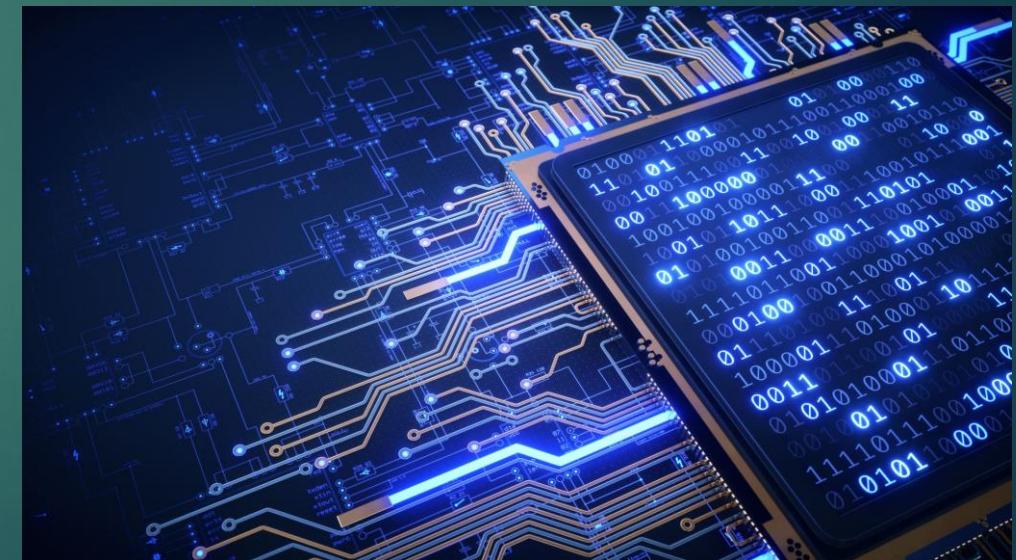


Brain Computer Interaction

Introduction to BCI



What's Today

- ▶ The Course Content
- ▶ What is Brain Computer Interaction
- ▶ History of BCI

Imagine a machine that records
feelings, emotions, even your
hopes and dreams.

And imagine that it can transfer
these experiences from
one mind to another...

B R A I N S T O R M¹⁵

METRO-GOLDWYN-MAYER presents

A J F PRODUCTION

A DOUGLAS TRUMBULL FILM "BRAINSTORM"
CHRISTOPHER WALKEN · NATALIE WOOD
LOUISE FLETCHER · CLIFF ROBERTSON

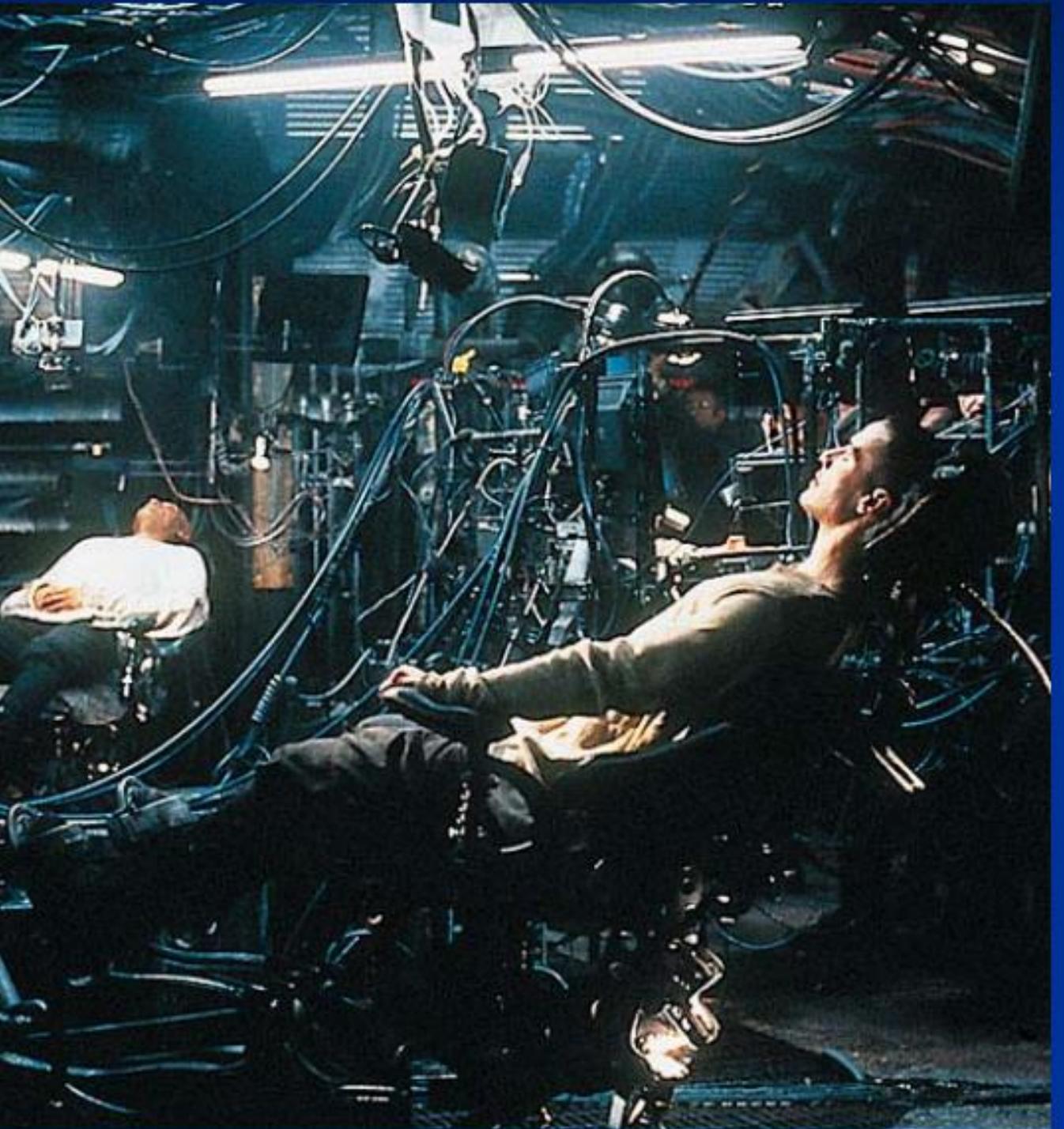
Screenplay
by ROBERT STITZEL and

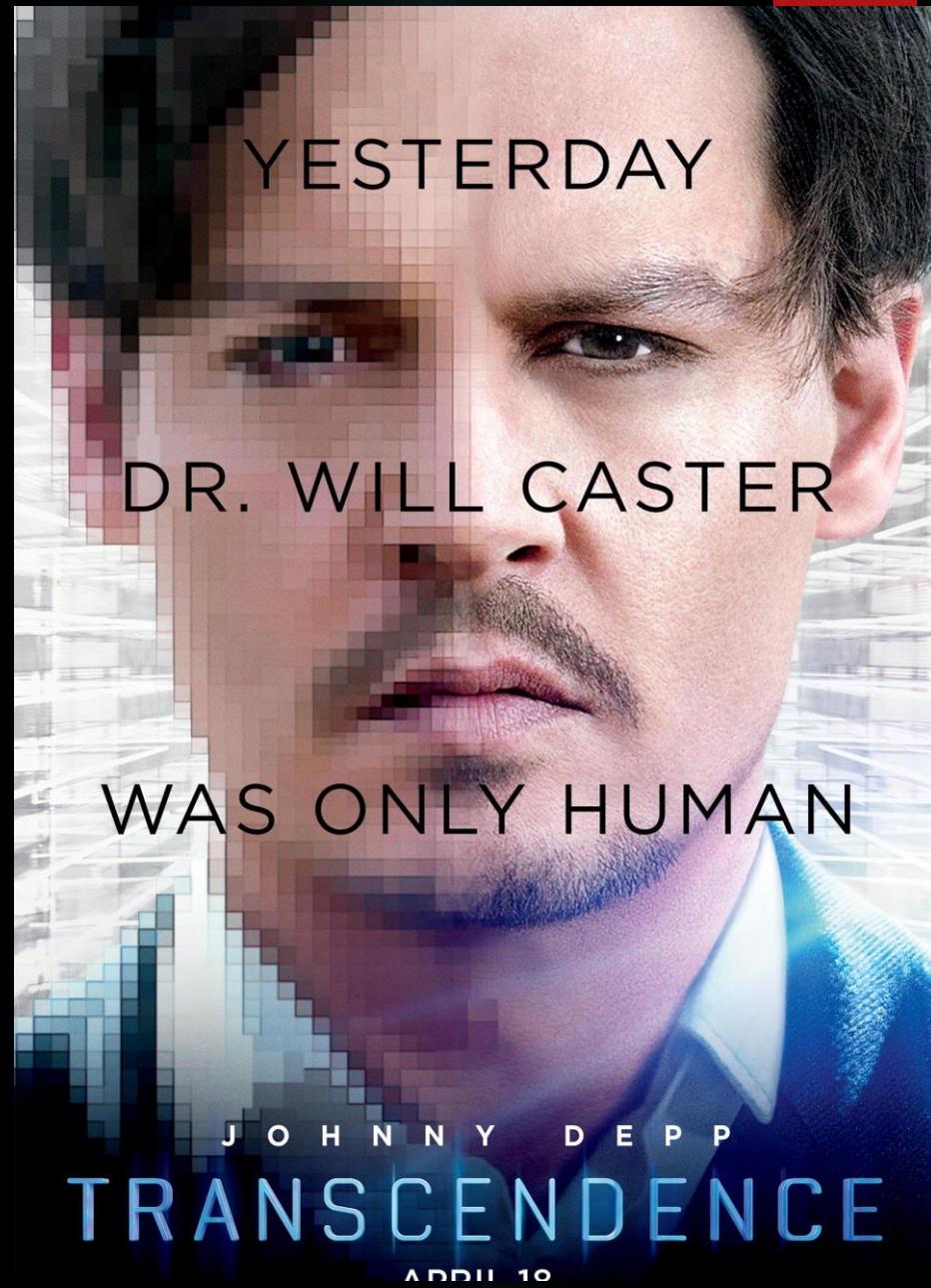
PHILIP FRANK MESSINA
Story by BRUCE JOEL RUBIN Music by JAMES HORNER

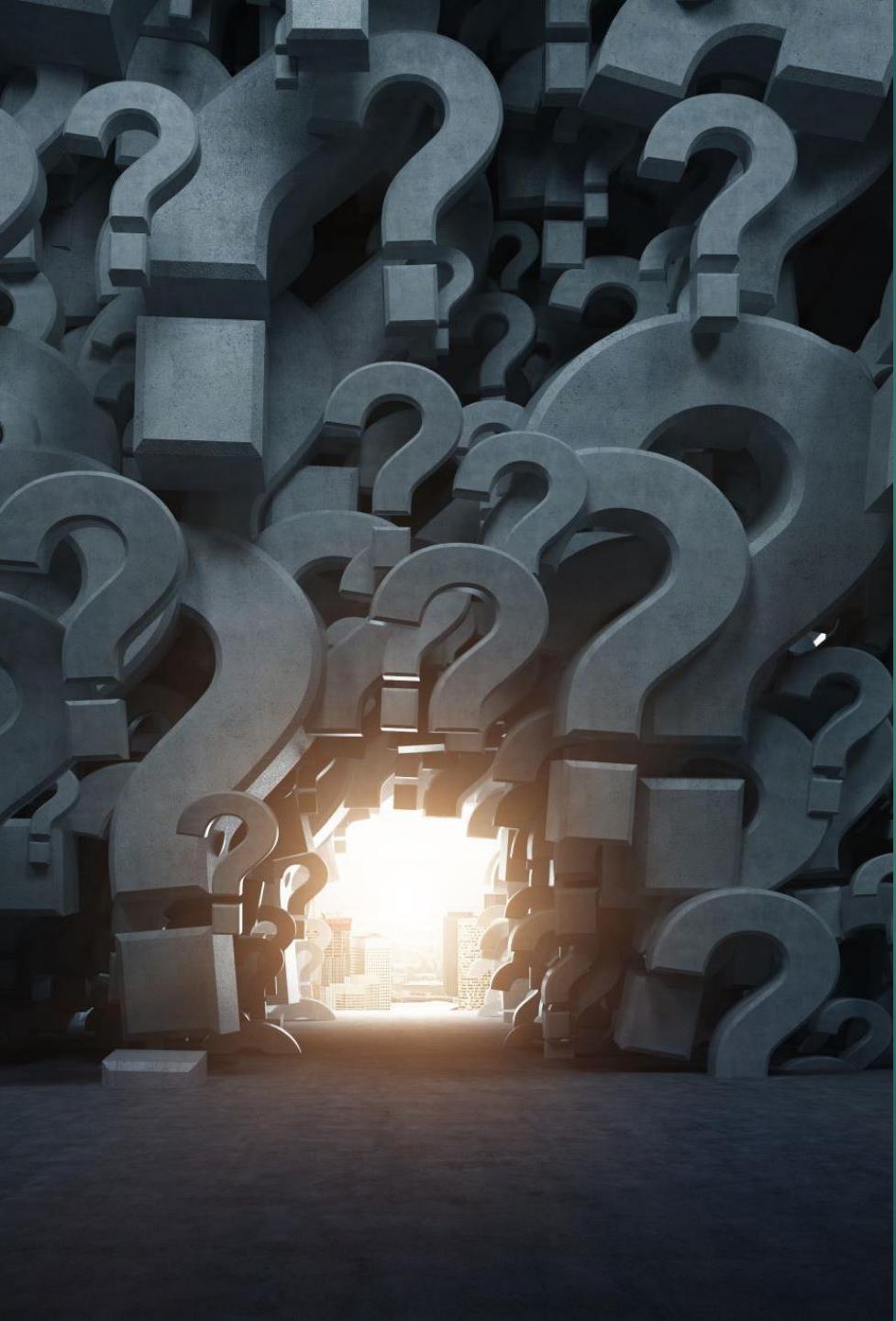
Director of Photography RICHARD YURICICH, A.S.C.

Executive in Charge of Production JACK GROSSBERG

Executive Joel L. Freedman







Is it FICTION
or is it
POSSIBLE???

Syllabus

Unit – 1

*Introduction to
Brain Computer
Interface*

Unit – 2

*Introduction to
Basic
Neuroscience*

Unit – 3 *Modelling
and Recoding of
the Brain Signals*

Unit – 4 *Signal
processing*

Unit – 5 *Signal
Analysis using
Machine Learning
Approaches*

Unit – 6 *BCI
Applications*

Course Assessment

- Mid Sem
- End Sem
- Quizzes
 - Surprise Quiz
 - Scheduled Quiz
- Projects
 - Knowledge of Python or MATLAB required

Motivation for BCIs

Potential for restoring lost sensory and motor function

To control prosthetic devices such as prosthetic arms or legs for amputees and patients with spinal-cord injuries

Wheelchairs for paralyzed individuals

Cursors and word spellers for communication by locked-in patients

Sensory prosthetic devices such as cochlear implant for the deaf, retinal implant for the blind

More recently, researchers have begun exploring BCIs for able-bodied individuals for a host of applications such as Game, Entertainment to robotic avatars, biometric identification and Education.

Users



Novice user



Language illiterate



Old-age people



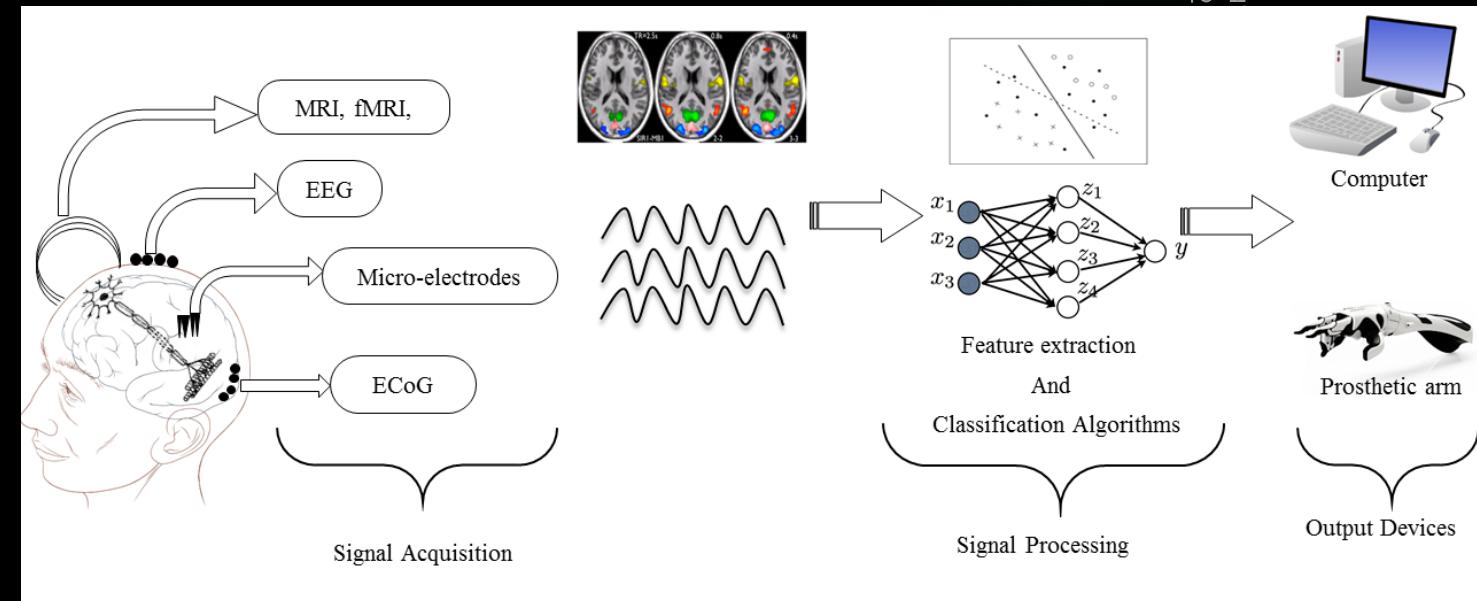
Blind user



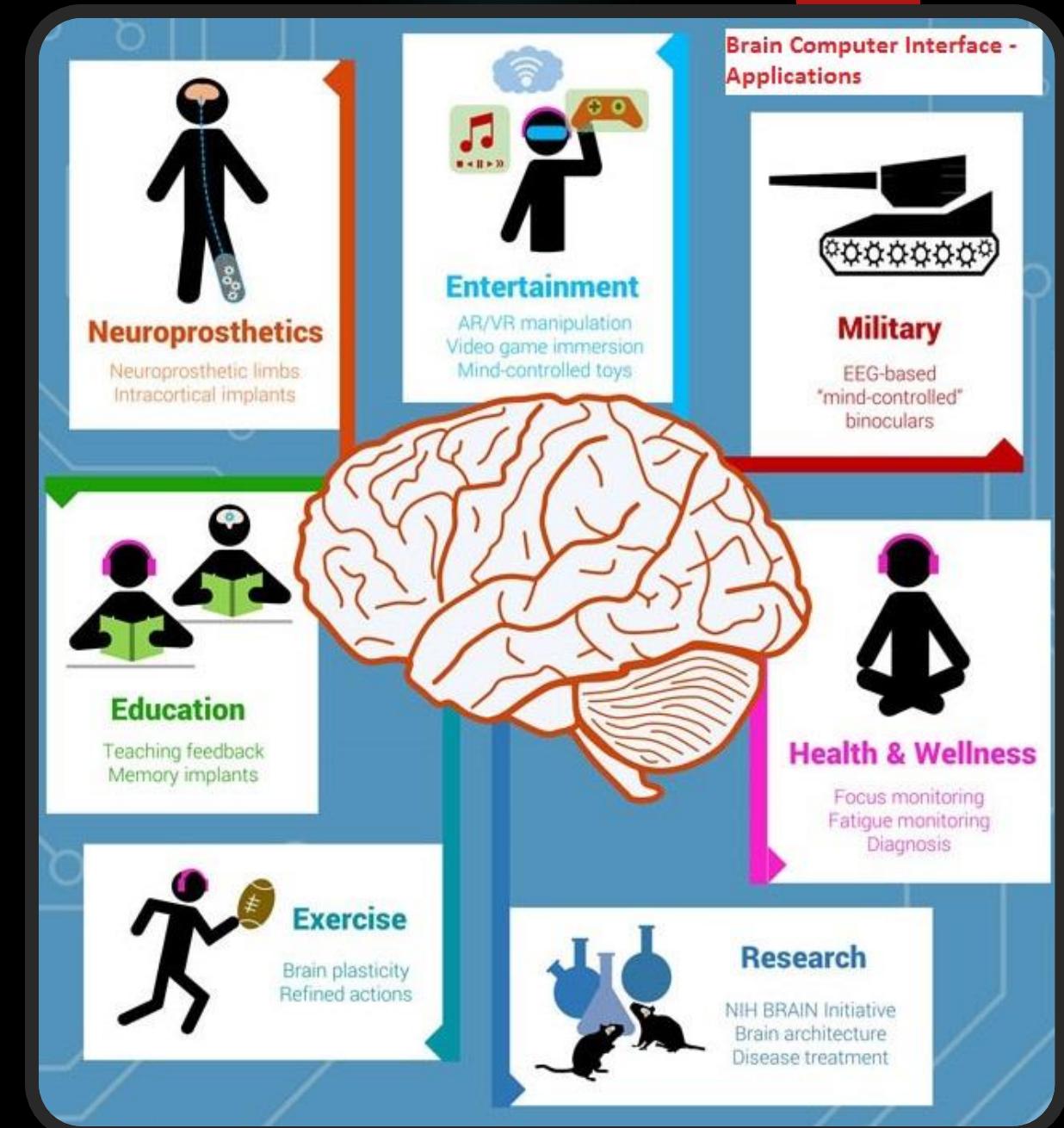
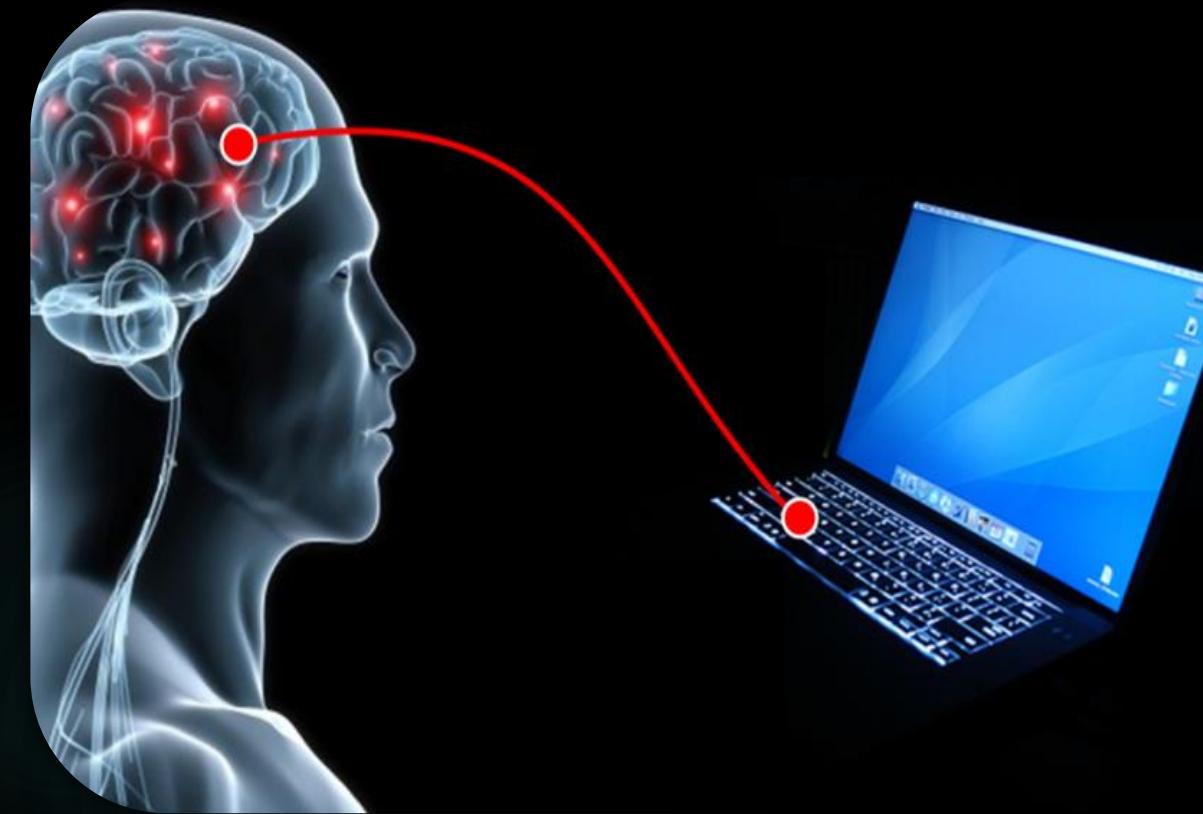
Disabled user

Brain Computer Interface

- ▶ A system which translates thoughts and provides an interface used for communication called as Brain Computer Interface (BCI)
- ▶ A typical BCI system comprises of signal acquisition system, signal processing (feature extraction and classification) and an output device



Brain Computer Interaction



Some real-time BCI Applications



Communication



Device Control



Automatic Motion Controlling



Attention Monitoring



Games & Entertainment

Whether BCIs will eventually become as commonplace as current human accessories for sensory and motor augmentation, such as cellular phones and automobiles.????

That remains to be seen.

There are several moral and ethical challenges that society will need to address



History of Brain Computer Interaction

Timeline of BCI

1875

Electrical impulses from a living brain of a rabbit and monkey were recorded for the first time by Richard Caton

1913

Napoleon Cybulski studied the flow of electric current in muscles using his own capacitor.

1969

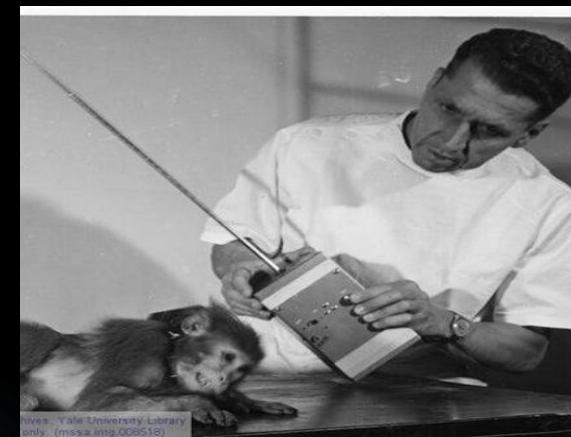
Delgado developed an implantable chip (which he called a “stimoceiver”) that could be used to both stimulate the brain by radio and send electrical signals of brain activity by telemetry, allowing the subject to move about freely.

Adolf Beck studied the brain activity of animals in response to sensory simulation

1890

Hans Berger recorded EEG signals from the lesion area of the human scalp for the first time using a Siemens double-coil galvanometer and non-polarized electrodes.

1920



**1969**

Dr. Eberhard Fetz showed that neural activity could be used to drive an external device.

1990

Philip Kennedy had in 1990 developed “invasive” human brain-computer interface, wires inside the brain attached to a computer.

2004

In 2004, Jonathan Wolpaw and researchers at New York State Department of Health’s Wadsworth Center demonstrated the ability to control a computer using a BCI.

Vidal in 1973 explored the use of scalp-recorded brain signals in humans to implement a simple noninvasive BCI based on “visually evoked potentials”

1973

John Donoghue and his team of Brown University in 2001, commercially design a brain computer interface, the so-called BrainGate.

2001

Phil Kennedy implanted electrodes into his brain in order to establish a connection between his motor cortex and a computer

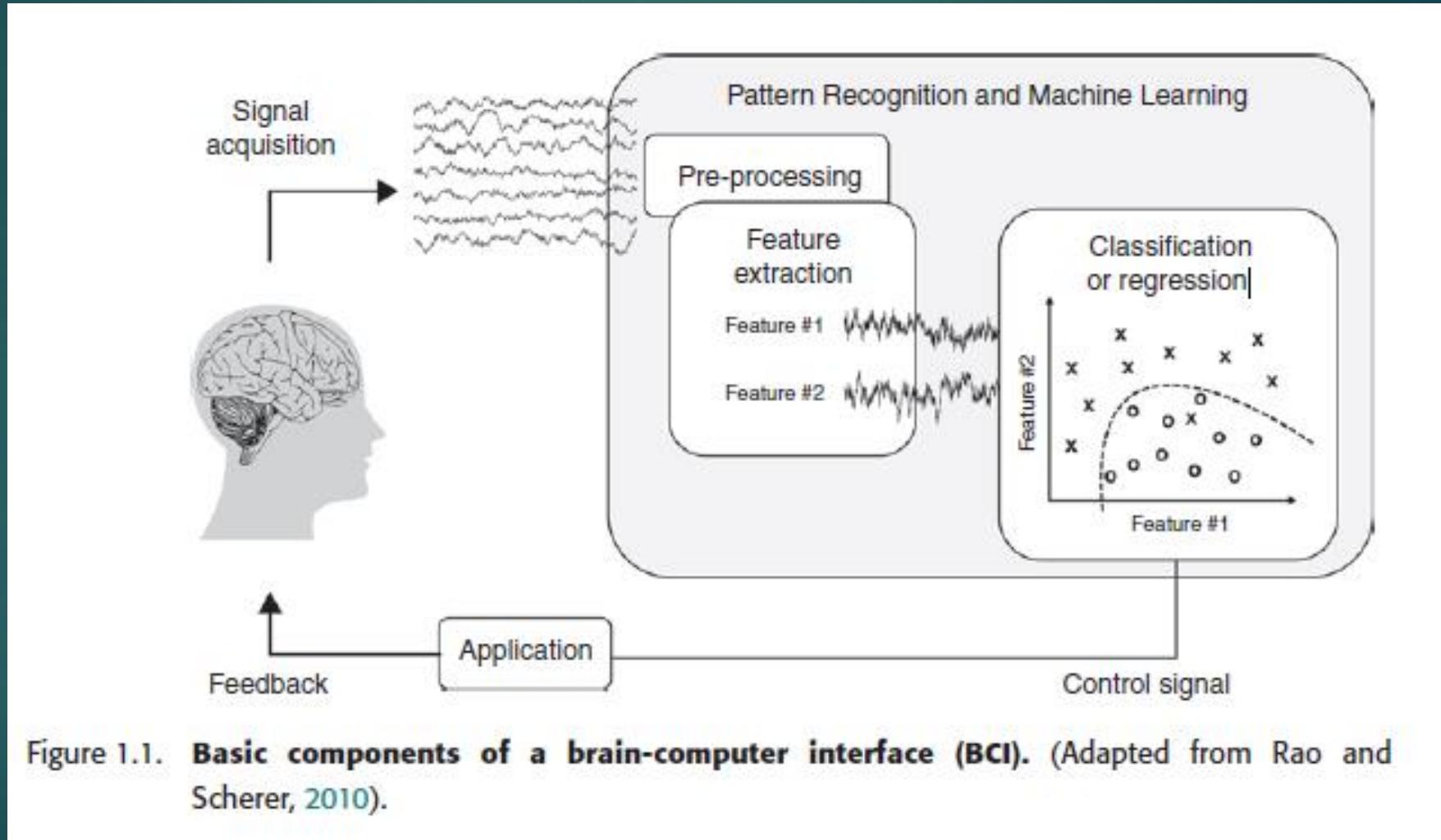
June 2014

To Study the Brain, a Doctor Puts Himself Under the Knife

How one of the inventors of brain-computer interfaces ended up getting one himself.

- ▶ More recently, researchers have begun exploring BCIs for able-bodied individuals for a host of applications such as
 - ▶ Games
 - ▶ Entertainment to robotic avatars, biometric identification,
 - ▶ and Education.

Our Goal in this course



BCI Applications



Hype Cycle for Emerging Technologies, 2020



BCI Applications

- ▶ Device Control
- ▶ User State Monitoring
- ▶ Training and Education
- ▶ Games and Entertainment.
- ▶ Cognitive improvement
- ▶ Safety and Security

Medical Applications



Device controls

- ▶ For rehabilitation
 - ▶ Prosthetic arm
 - ▶ Prosthetic legs

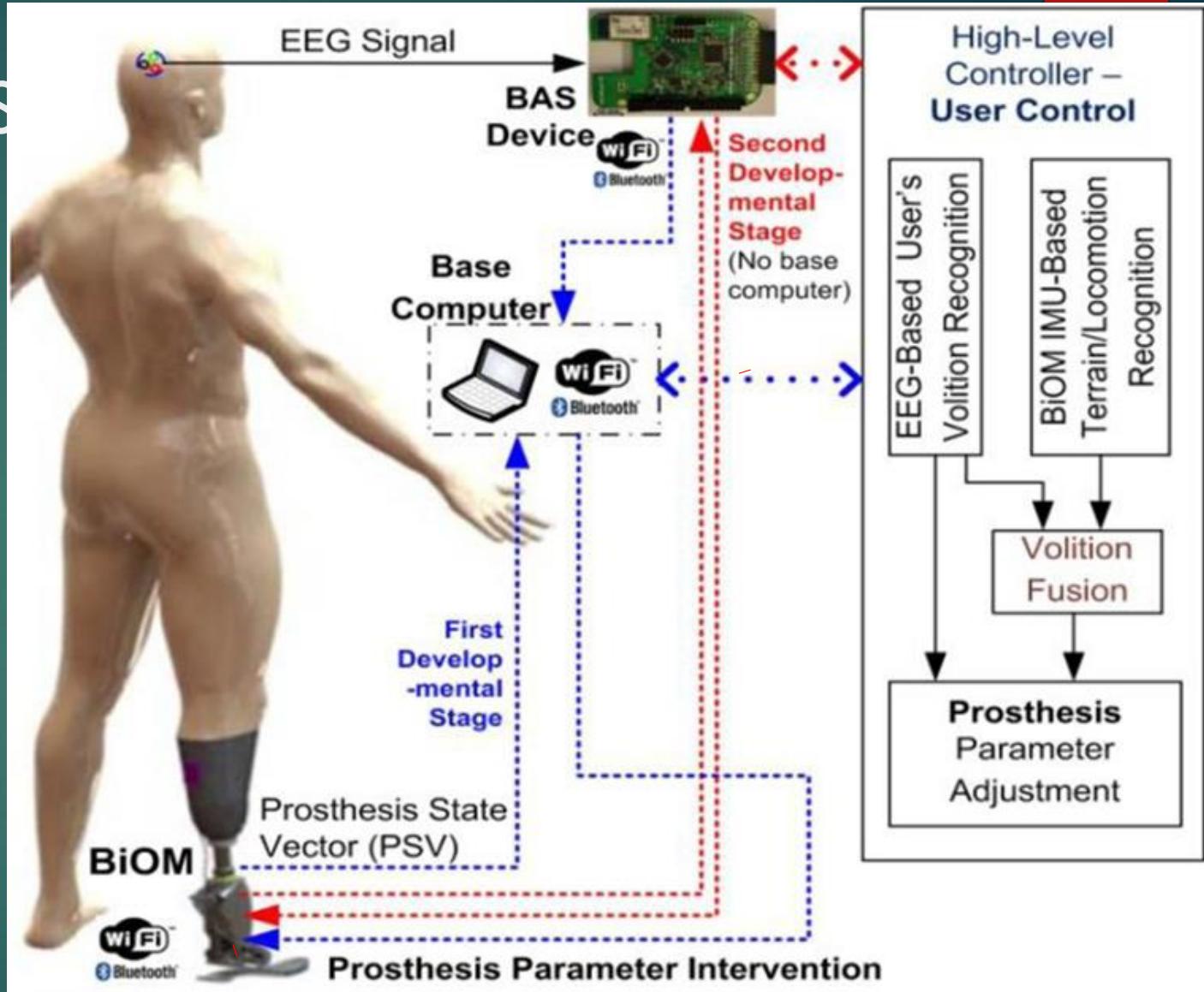
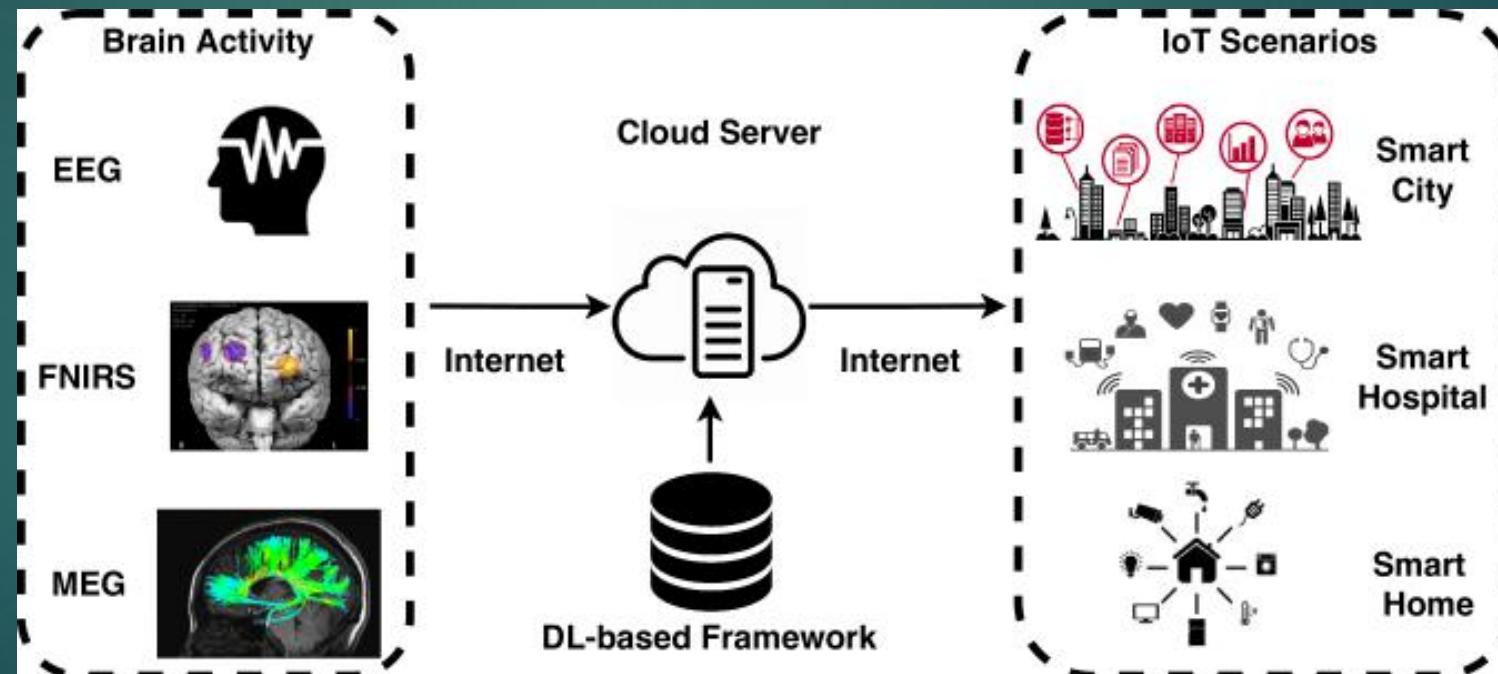


Image credits:

https://www.frontiersin.org/files/Articles/308916/fneur-08-00696-HTML/image_m/fneur-08-00696-g001.jpg

Neuroergonomics and smart environment

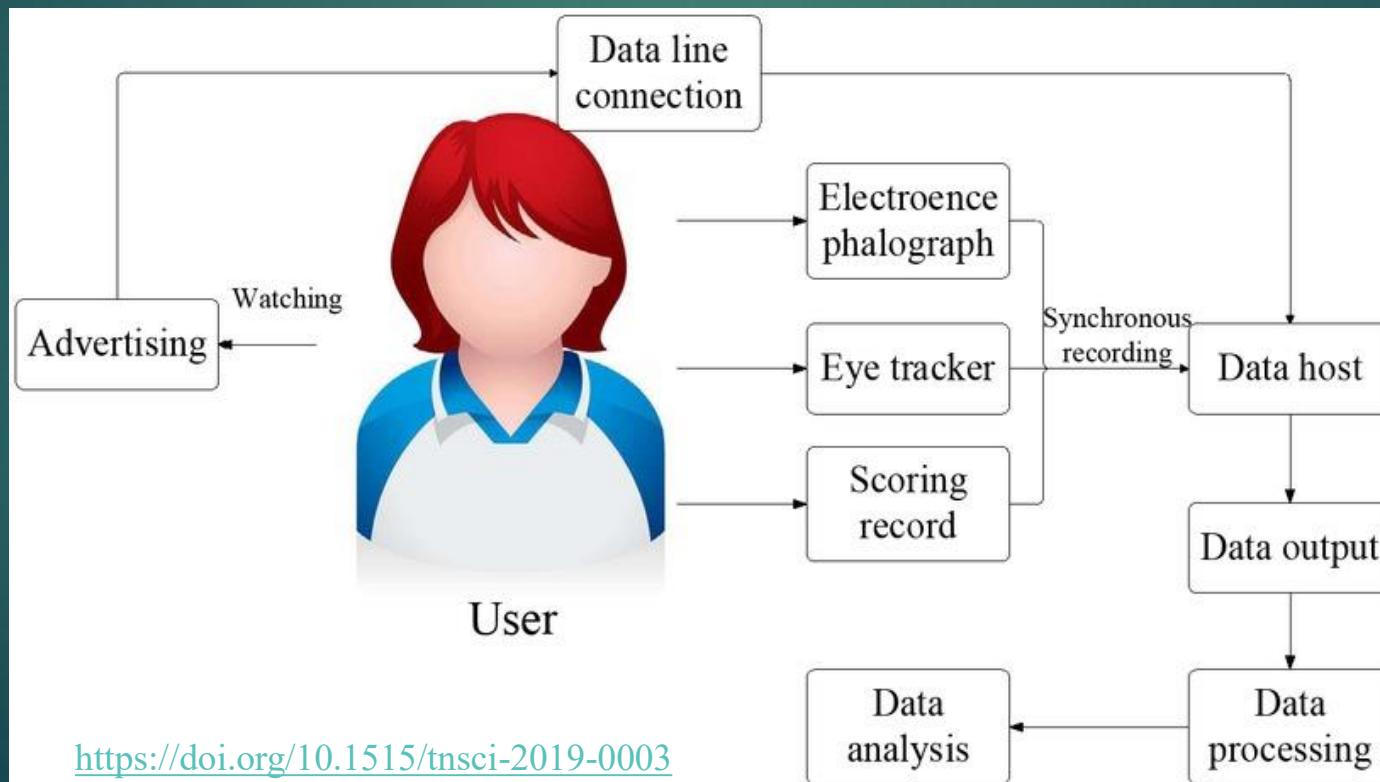
- ▶ Cooperation between Internet of Things (IOT) and BCI technologies
- ▶ intelligent transportation



by [Xiang Zhang, et al.](#) ·

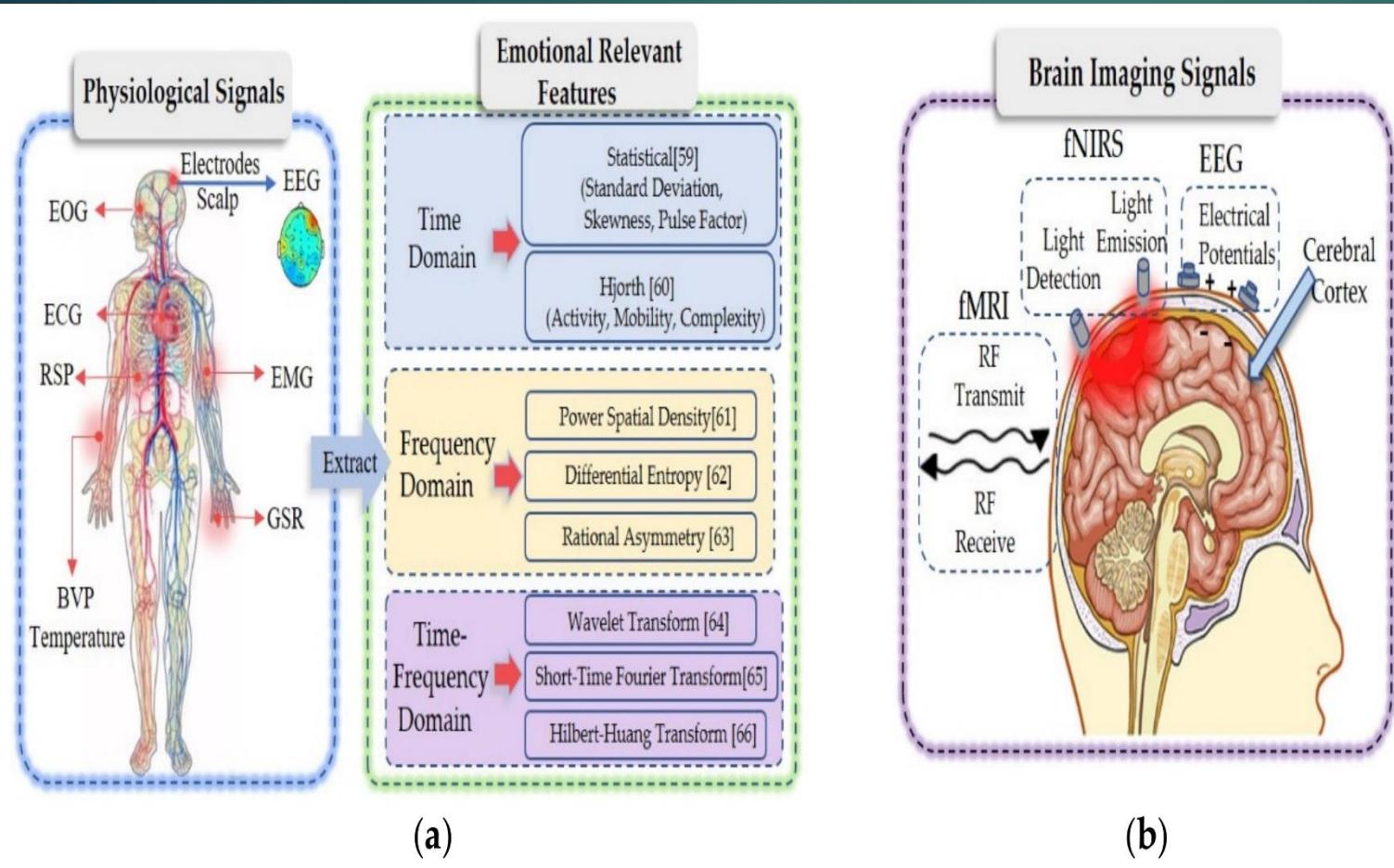
Neuromarketing and advertisement

- ▶ EEG evaluation for TV advertisements related to both commercial and political fields.
 - ▶ The generated attention accompanying watching activity
 - ▶ Estimating the memorization of TV advertisements



Educational and self-regulation

- ▶ Emotional regulation
 - ▶ Use of fMRI–EEG BCI to fight the depression feeling as well as other neuropsychiatric disorders



Challenges

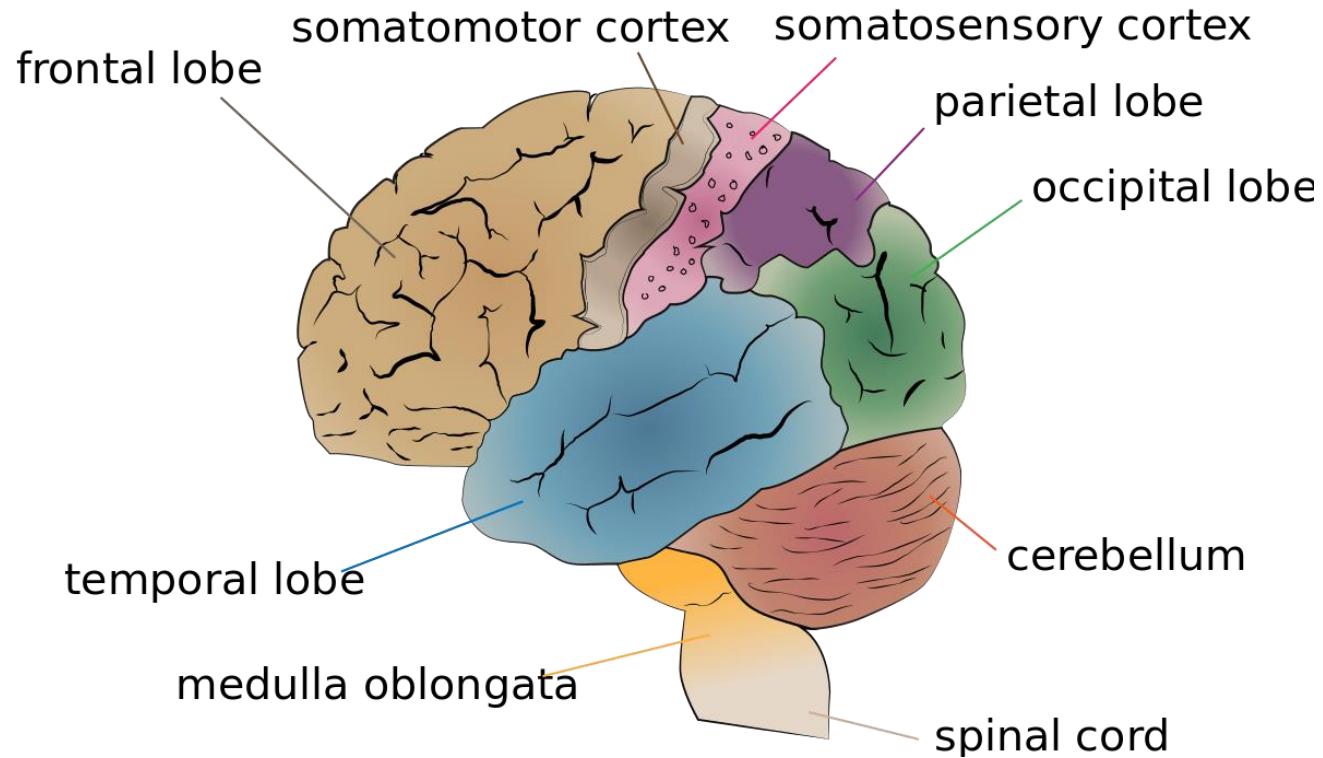
- ▶ Usability
- ▶ Hardware
- ▶ Signal processing
- ▶ System integration
- ▶ Cost

BCI-S2022

Basics of Neuroscience for BCI



The Human Brain





The Neuron

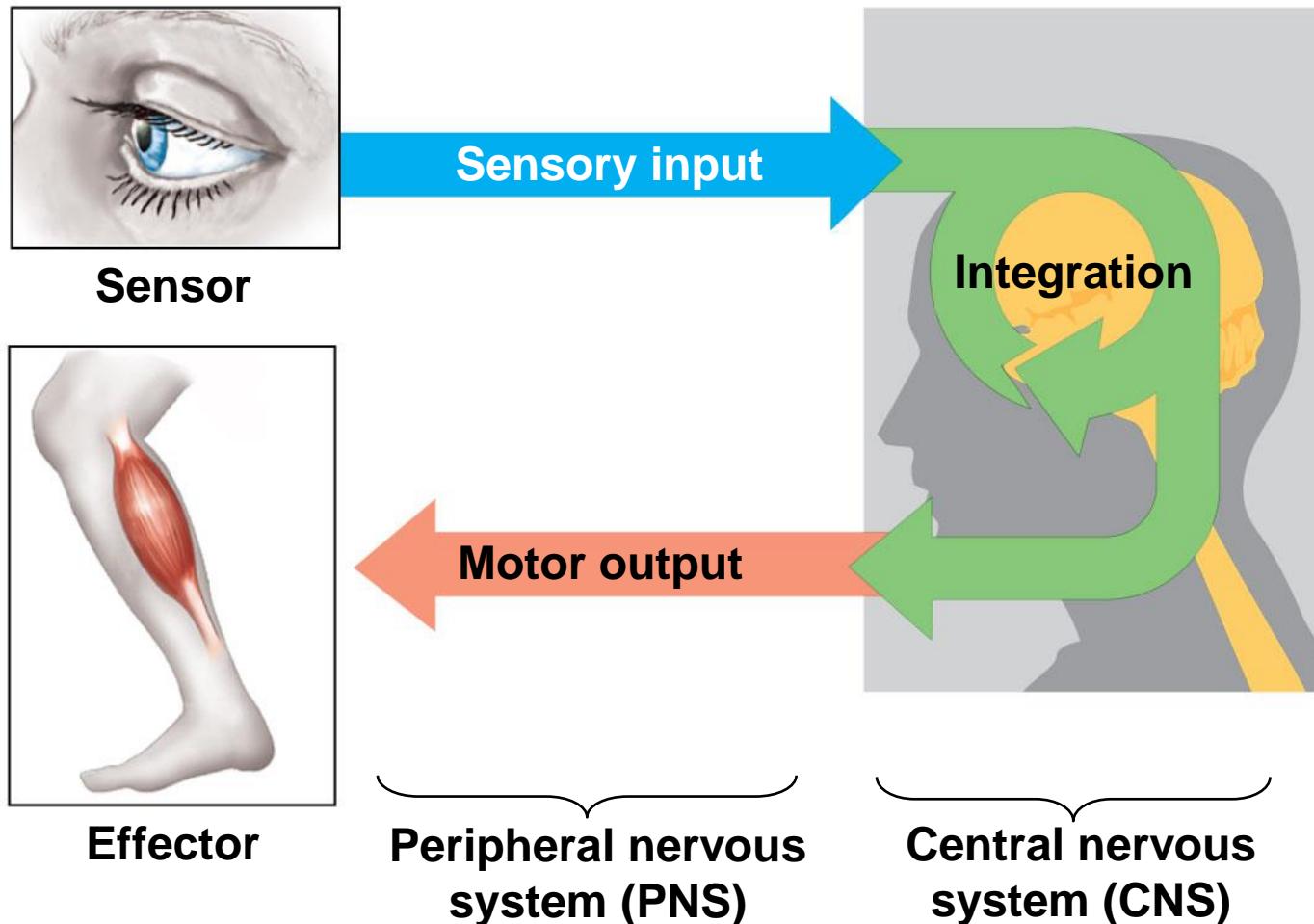
- The brain's unique information processing capabilities arise from its massively parallel and distributed way of computing.
- The workhorse of the brain is a type of cell known as a **NEURON**.
- Neuron is a complex electrochemical device that receives information from hundreds of other neurons, processes this information, and conveys its output to hundreds of other neurons



The Neuron

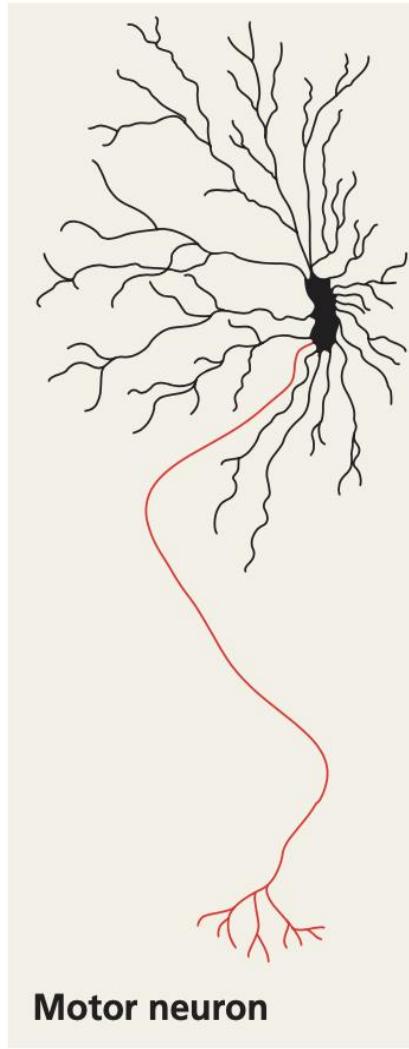
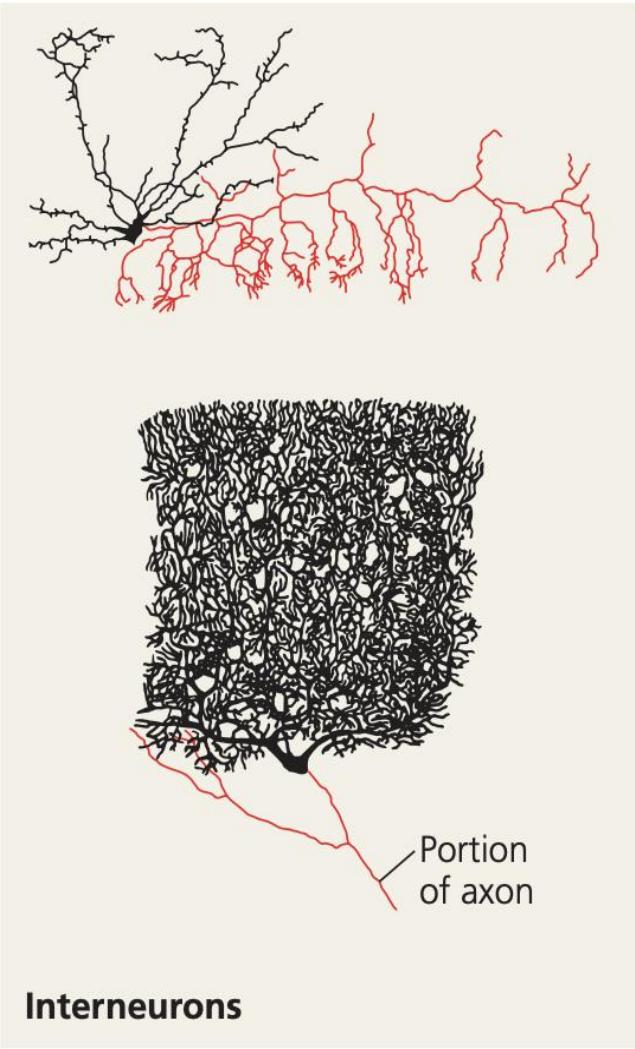
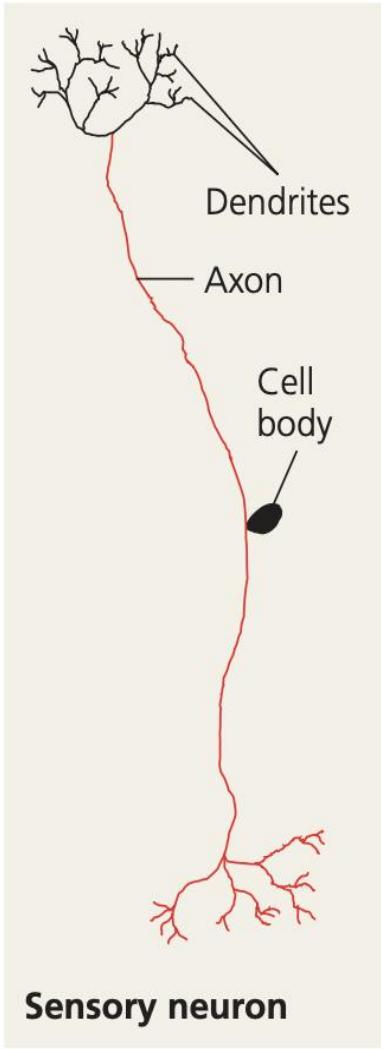
- The neuron can be regarded as a leaky bag of charged liquid.
- The membrane of a neuron is made up of a lipid bi-layer that is impermeable except for openings called ionic channel.
- The ionic channels selectively allow the passage of a few ions

REVISIT : Introduction to Information Processing



Many animals have a complex nervous system that consists of

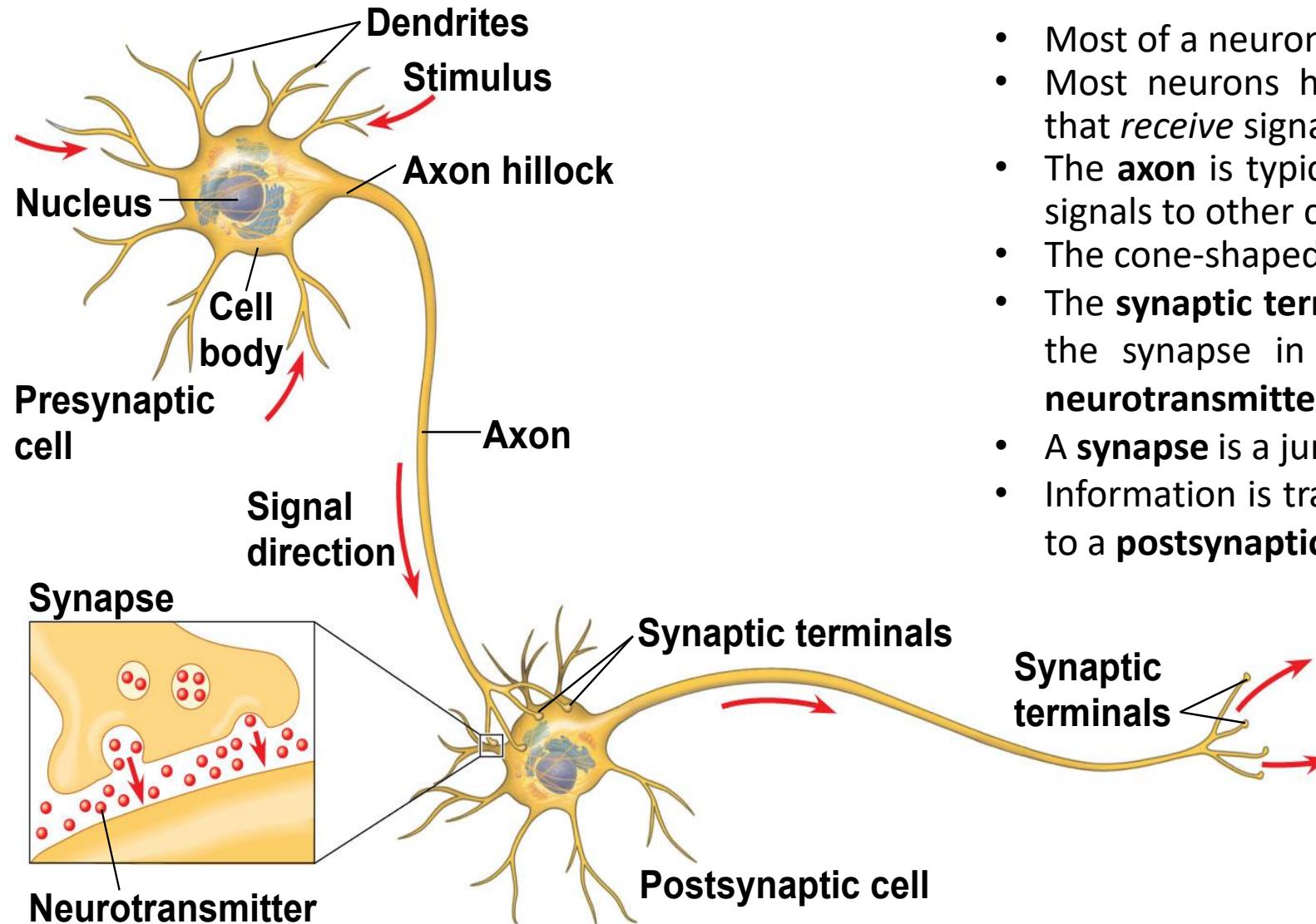
- A **central nervous system (CNS)** where integration takes place; this includes the brain and a nerve cord
- A **peripheral nervous system (PNS)**, which carries information into and out of the CNS
- The neurons of the PNS, when bundled together, form **nerves**



- Sensors detect external stimuli and internal conditions and transmit information along **sensory neurons**
- Sensory information is sent to the brain, where **interneurons** integrate the information
- Motor output leaves the brain via **motor neurons**, which trigger muscle or gland activity

Structural diversity of neurons. Cell bodies and dendrites are black in these diagrams; axons are red. In the sensory neuron, unlike the other neurons here, the cell body is located partway along the axon that conveys signals from the dendrites to the axon's terminal branches.

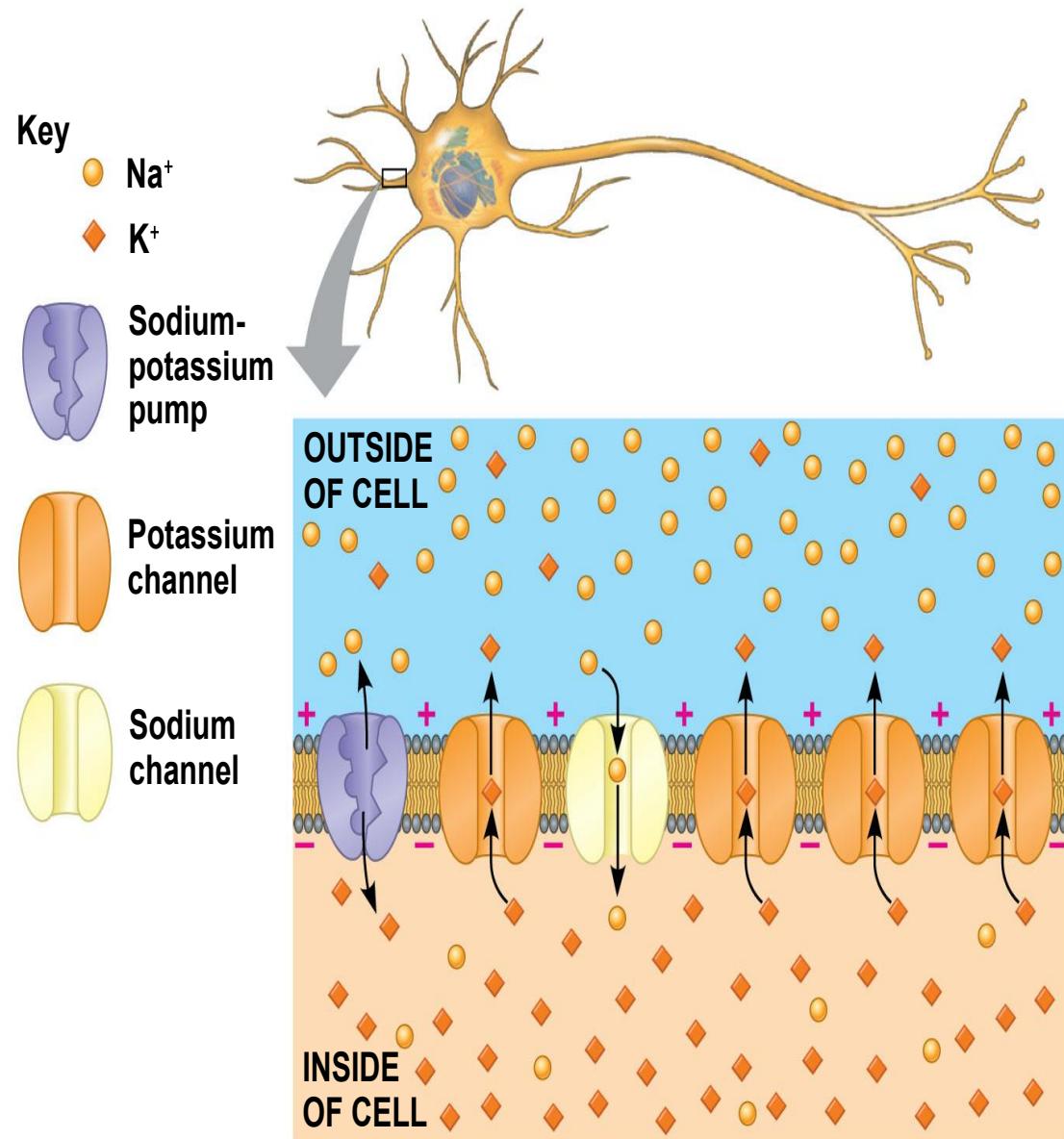
Neuron Structure and Function



- Most of a neuron's organelles are in the **cell body**.
- Most neurons have **dendrites**, highly branched extensions that *receive* signals from other neurons.
- The **axon** is typically a much longer extension that transmits signals to other cells at synapses.
- The cone-shaped base of an axon is called the **axon hillock**.
- The **synaptic terminal** of one axon passes information across the synapse in the form of chemical messengers called **neurotransmitters**.
- A **synapse** is a junction between an axon and another cell
- Information is transmitted from a **presynaptic cell** (a neuron) to a **postsynaptic cell** (a neuron, muscle, or gland cell).

Ion pumps and ion channels establish the resting potential of a neuron

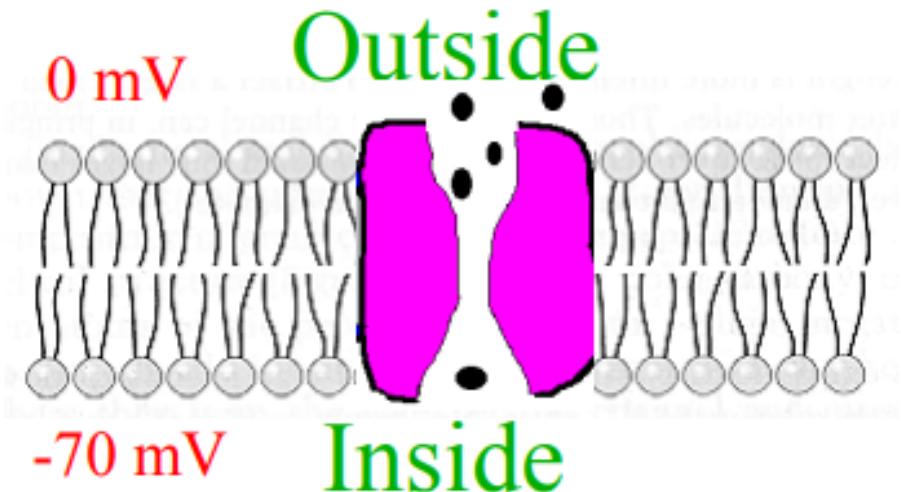
- Every cell has a voltage (difference in electrical charge) across its plasma membrane called a **membrane potential**.
- The **resting potential** is the membrane potential of a neuron not sending signals.
- Changes in membrane potential act as signals, transmitting and processing information.
- In a mammalian neuron at resting potential, the concentration of K^+ is highest inside the cell, while the concentration of Na^+ is highest outside the cell.
- The opening of **ion channels** in the plasma membrane converts chemical potential to electrical potential.
- A neuron at resting potential contains many open K^+ channels and fewer open Na^+ channels; K^+ diffuses out of the cell.
- The resulting buildup of negative charge within the neuron is the major source of membrane potential.



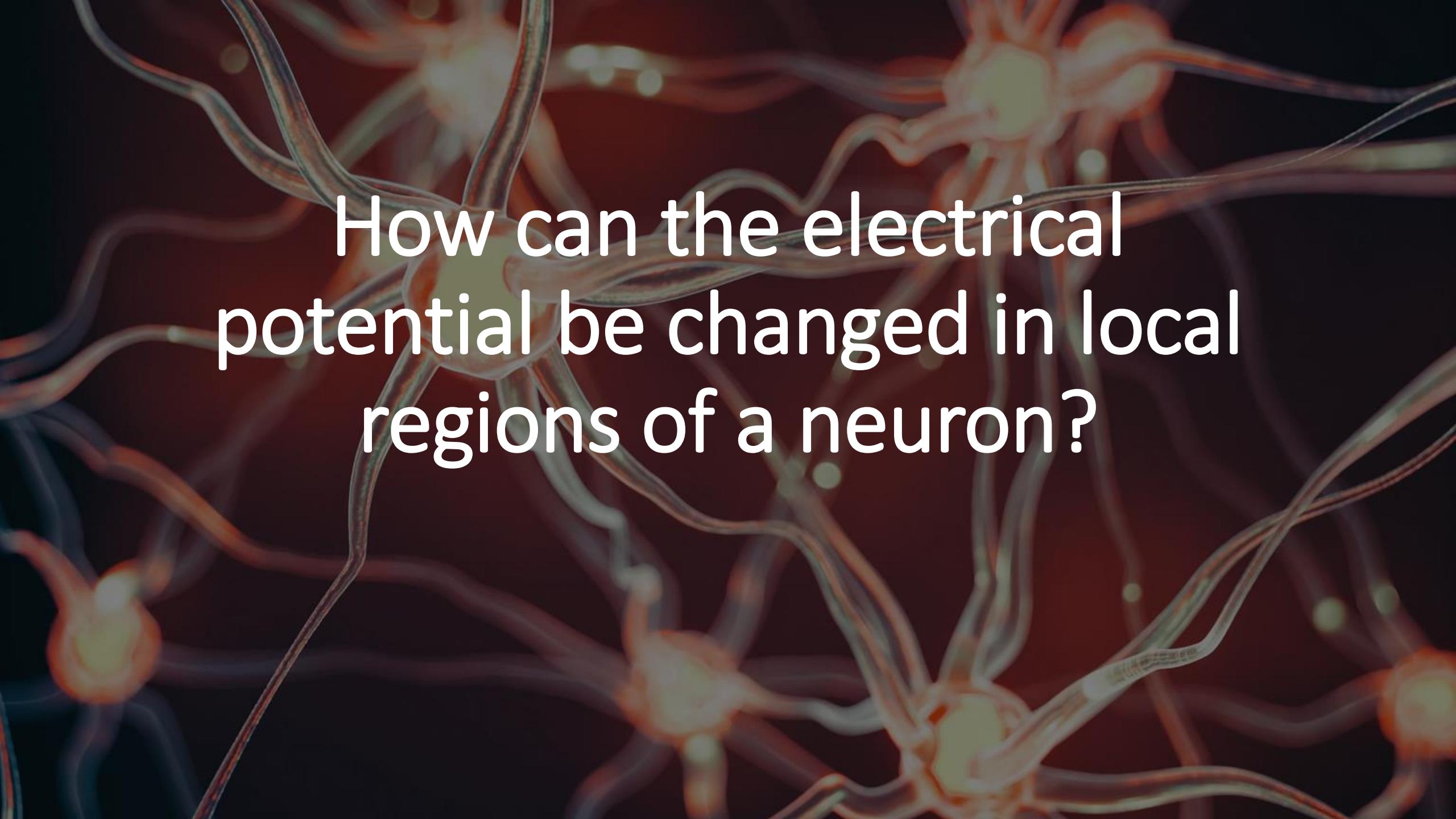
The Electrical Personality of a Neuron

- Each neuron maintains a potential difference across its membrane
- Inside is ± 70 to ± 80 mV relative to outside
- $[Na^+]$, $[Cl^-]$ and $[Ca^{2+}]$ higher outside; $[K^+]$ and organic anions $[A^-]$ higher inside
- Ionic pump maintains -70 mV difference by expelling Na^+ out and allowing K^+ ions in

$[Na^+]$, $[Cl^-]$, $[Ca^{2+}]$
 $[K^+]$, $[A^-]$



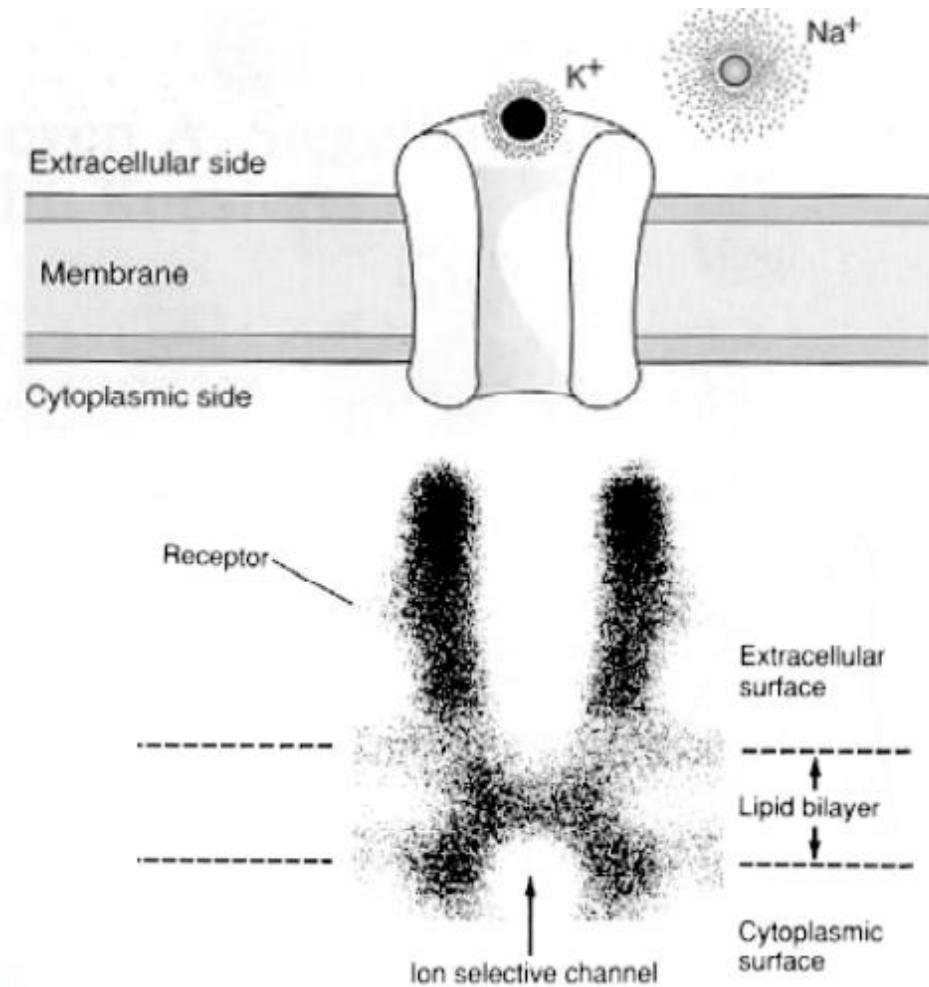
$[K^+]$, $[A^-]$
 $[Na^+]$, $[Cl^-]$, $[Ca^{2+}]$



How can the electrical potential be changed in local regions of a neuron?

Ionic Channels: The Gatekeepers

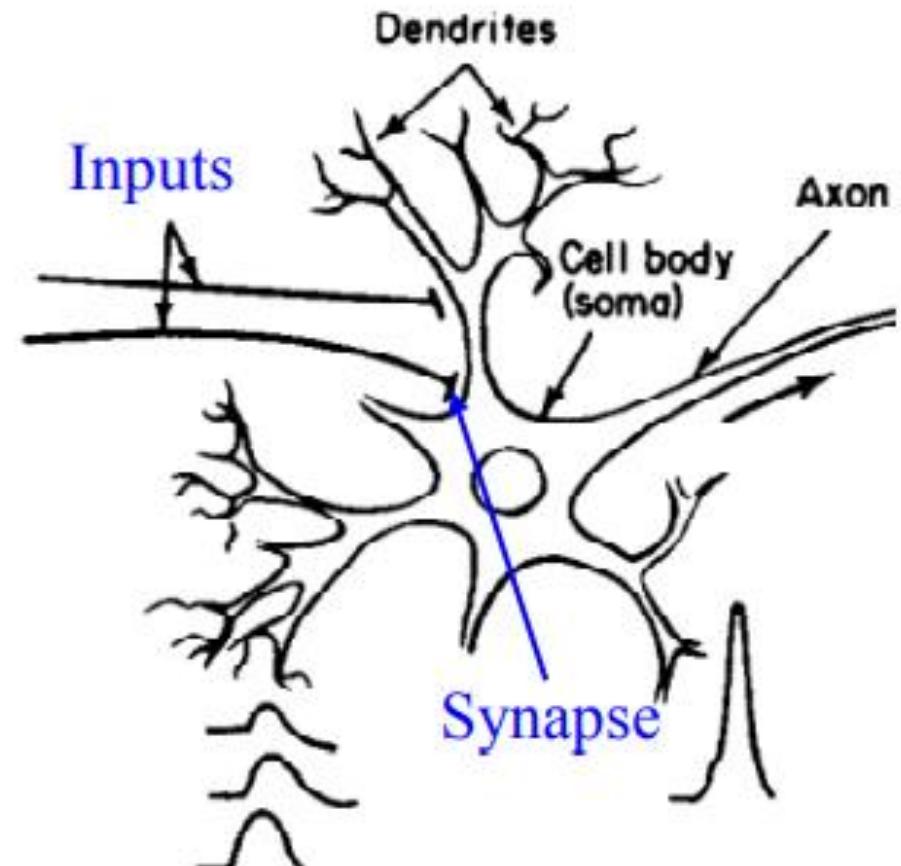
- Proteins in membranes act as channels that allow specific ions to pass through.
 - E.g.: Pass K⁺ but not Cl⁻ or Na⁺
- These **IONIC CHANNELS** are gated
 - Voltage-gated: Probability of opening depends on membrane voltage
 - Chemically-gated: Binding to a chemical causes channel to open
 - Mechanically-gated: Sensitive to pressure or stretch



From Kandel, Schwartz, Jessel, Principles of Neural Science, 3rd edn., 1991, pgs. 68 & 137

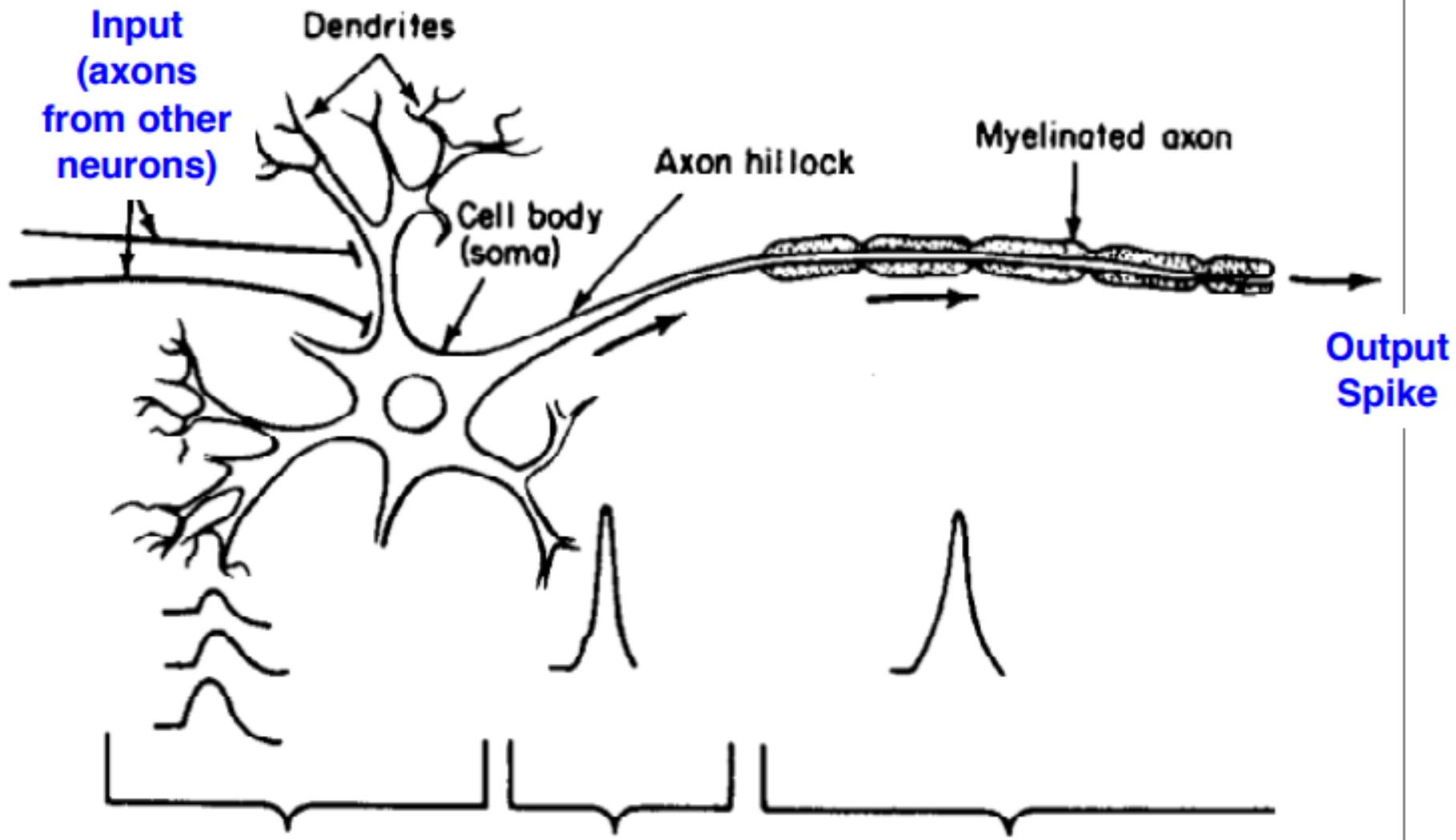
Gated Channels allow Neuronal Signaling

- Inputs from other neurons -> **chemically-gated channels** (at “**synapses**”) -> Changes in local membrane potential
- This causes opening/closing of **voltage-gated channels** in dendrites, body, and axon, resulting in **depolarization** (positive change in voltage) or **hyperpolarization** (negative change)



Regions of Neurons

- Neurons in different regions of the brain have different morphological structures
- The typical structure includes a **cell body** (called the soma) connected to a tree-like structure with branches called **dendrites**
- A single branch called the **axon** that emanates from the soma and conveys the output spike to other neurons.
- The **spike** is typically initiated near the junction of the soma and axon and propagates down the length of the axon.
- Many axons are covered by **myelin**, a white sheath that significantly boosts the speed of propagation of the spike over long distances.



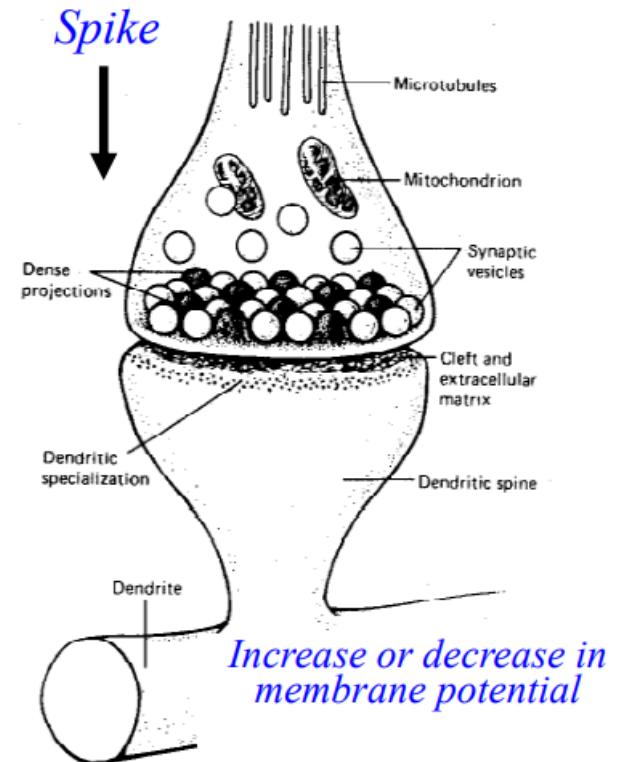
(EPSP = Excitatory Post-Synaptic Potential)

Trigger:
all-or-none
spike initiated

Conducted all-or-none spike
(conduction of spike to next cell)

Synapse

- Neurons communicate with each other through connections known as **synapses**.
- Synapses can be **electrical** but are more typically **chemical**.
- A synapse is essentially a gap or cleft between the axon of one neuron (called the **presynaptic neuron**) and a dendrite (or soma) of another neuron (called the **postsynaptic neuron**)



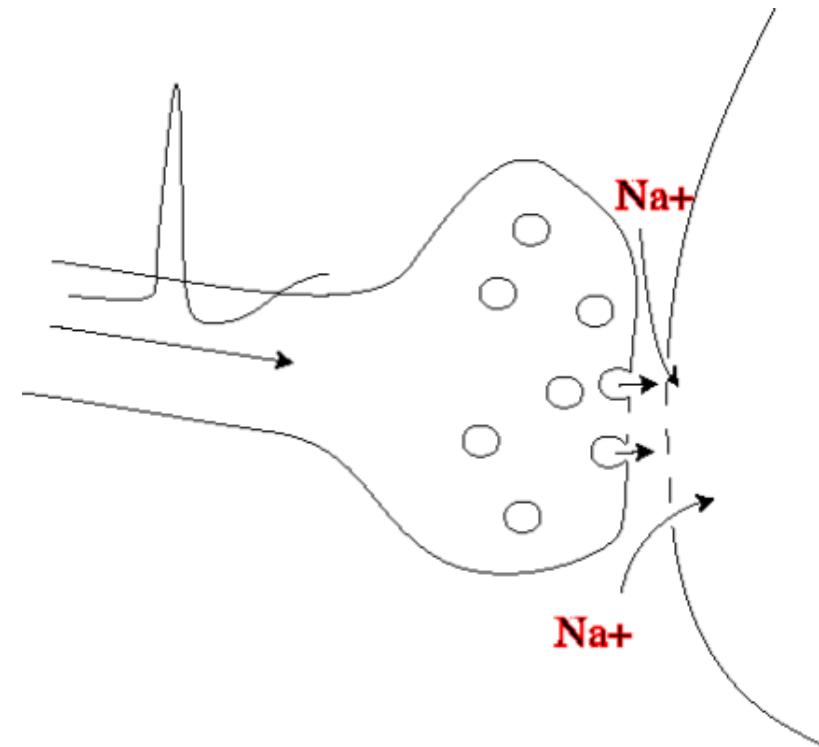
Synapse

- When an action potential arrives from a presynaptic neuron, it causes the release of chemicals known as **neurotransmitters** into the synaptic cleft.
- These chemicals in turn bind to the ionic channels (or receptors) on the postsynaptic neuron, causing these channels to open, thereby influencing the local membrane potential of the postsynaptic cell.

Synapse

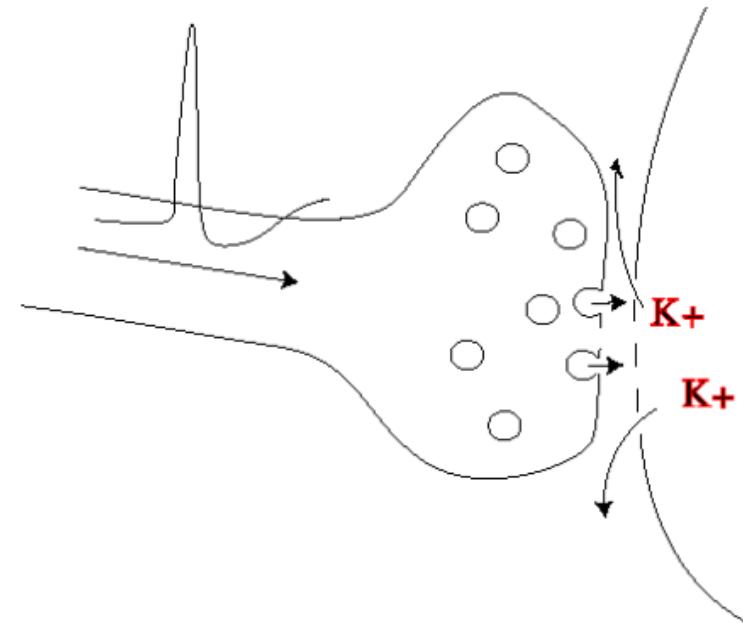
- Synapses can be **excitatory** or **inhibitory**.
- **Excitatory** synapses cause a momentary increase in the local membrane potential of the postsynaptic cell.
 - This increase is called an **excitatory postsynaptic potential** (EPSP).
 - EPSPs contribute to a higher probability of firing a spike by the postsynaptic cell.
- **Inhibitory** synapses do the opposite, temporarily decrease the local membrane potential of the postsynaptic cell
 - They cause **inhibitory postsynaptic potentials** (IPSPs)
- A neuron is called **excitatory** or **inhibitory** based on the kind of synapse it forms with postsynaptic neurons

An Excitatory Synapse



Input spike →
Neurotransmitter release →
Binds to Na channels (which open) →
Na+ influx →
Depolarization due to EPSP (excitatory postsynaptic potential)

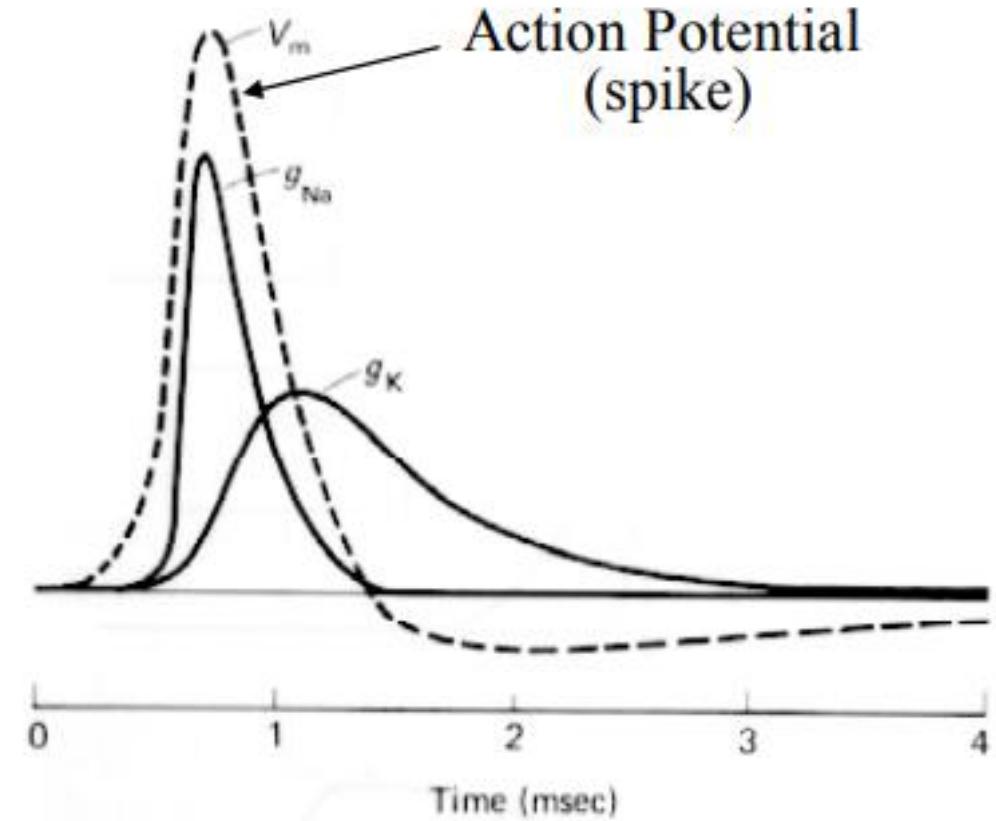
An Inhibitory Synapse



Input spike →
Neurotransmitter release →
Binds to K channels →
 K^+ leaves cell →
Hyperpolarization due to IPSP (inhibitory postsynaptic potential)

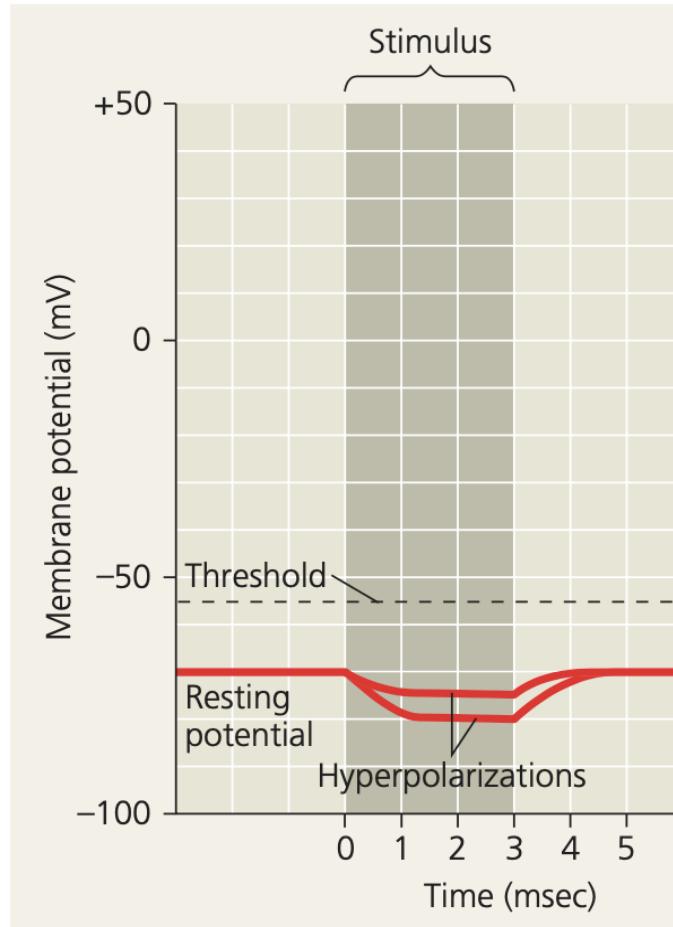
Action Potential or Spikes

- When the neuron receives sufficiently strong inputs from other neurons a cascade of events is triggered
- Rapid **influx of Na⁺** ions into the cell
 - *Causing the membrane potential to rise rapidly.*
- The opening of K⁺ channels triggers the **outflux of K⁺ ions**
 - *Causing a drop in the membrane potential.*
- This rapid **rise** and **fall** of the membrane potential is called an **action potential** or **spike** and represents the dominant mode of communication between one neuron and another.

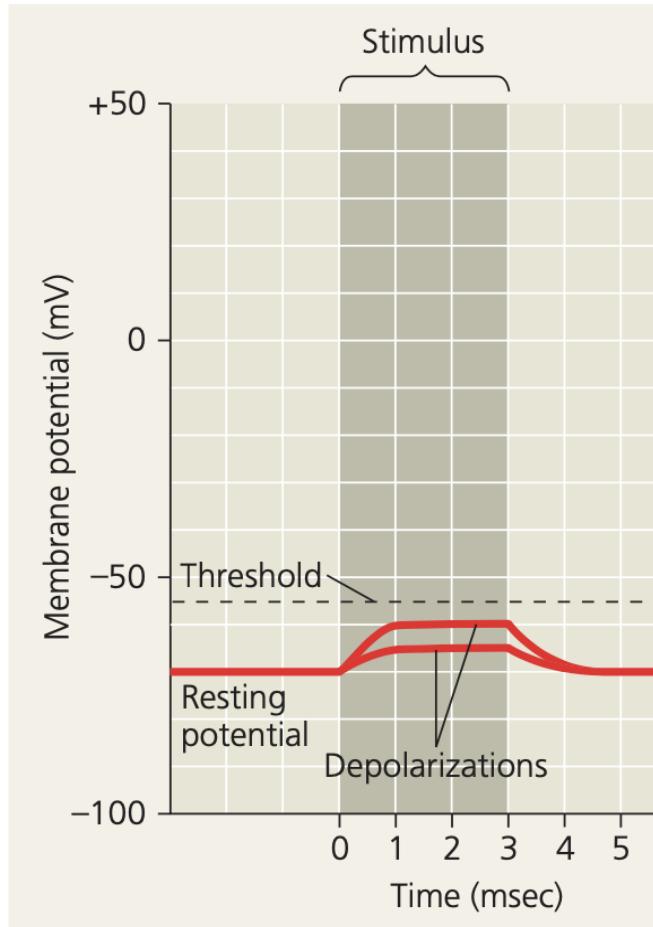


From Kandel, Schwartz, Jessel, Principles of Neural Science, 3rd edn., 1991, pg. 110

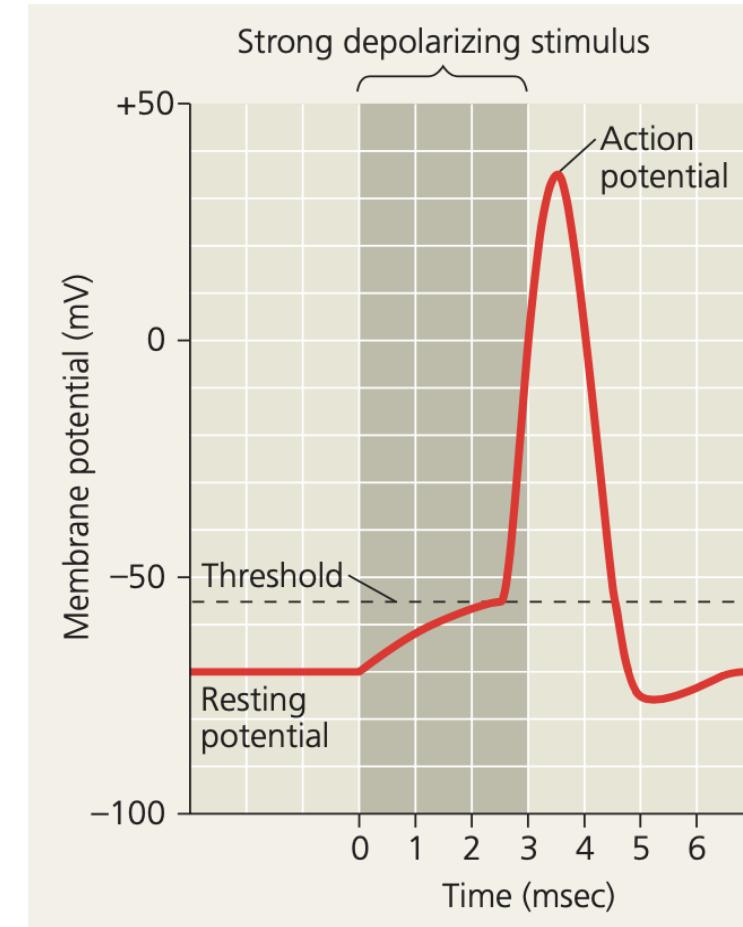
Graded potentials and an action potential in a neuron.



(a) Graded hyperpolarizations produced by two stimuli that increase membrane permeability to K^+ . The larger stimulus produces a larger hyperpolarization.



(b) Graded depolarizations produced by two stimuli that increase membrane permeability to Na^+ . The larger stimulus produces a larger depolarization.



(c) Action potential triggered by a depolarization that reaches the threshold.

Spike Generation

- The generation of a spike by a neuron involves a complex cascade of events involving sodium and potassium channels
- This process can be simplified into a simple threshold model of spike generation.
 - *When the neuron receives sufficiently strong inputs from its synapses for its membrane potential to cross a neuron-specific threshold, a spike is emitted.*

Synaptic plasticity: Adapting the connections

- **Long Term Potentiation (LTP):** Increase in synaptic strength of a synaptic connection between two neurons caused by correlated firing of the two neurons
 - lasts for several hours or more.
- Measured as an increase in the excitatory postsynaptic potential (EPSP) caused by presynaptic spikes
- LTP has been found in several brain areas including the hippocampus and the neocortex.
- Note: *LTP is regarded as a biological implementation of Donald Hebb's famous postulate (also called Hebbian learning or Hebbian plasticity) that if a neuron A is consistently involved in causing another neuron B to fire, then the strength of the connection from A to B should be increased.*

Synaptic plasticity: Adapting the connections

- **Long-term depression or LTD:** Decrease in the strength of a synaptic connection caused
 - by uncorrelated firing between the two neurons involved.
 - Reduction in synaptic strength that lasts for several hours or more
- LTD has been observed most prominently in the cerebellum, although it also coexists with LTP in the hippocampus, neocortex, and other brain areas

Synaptic plasticity: Adapting the connections

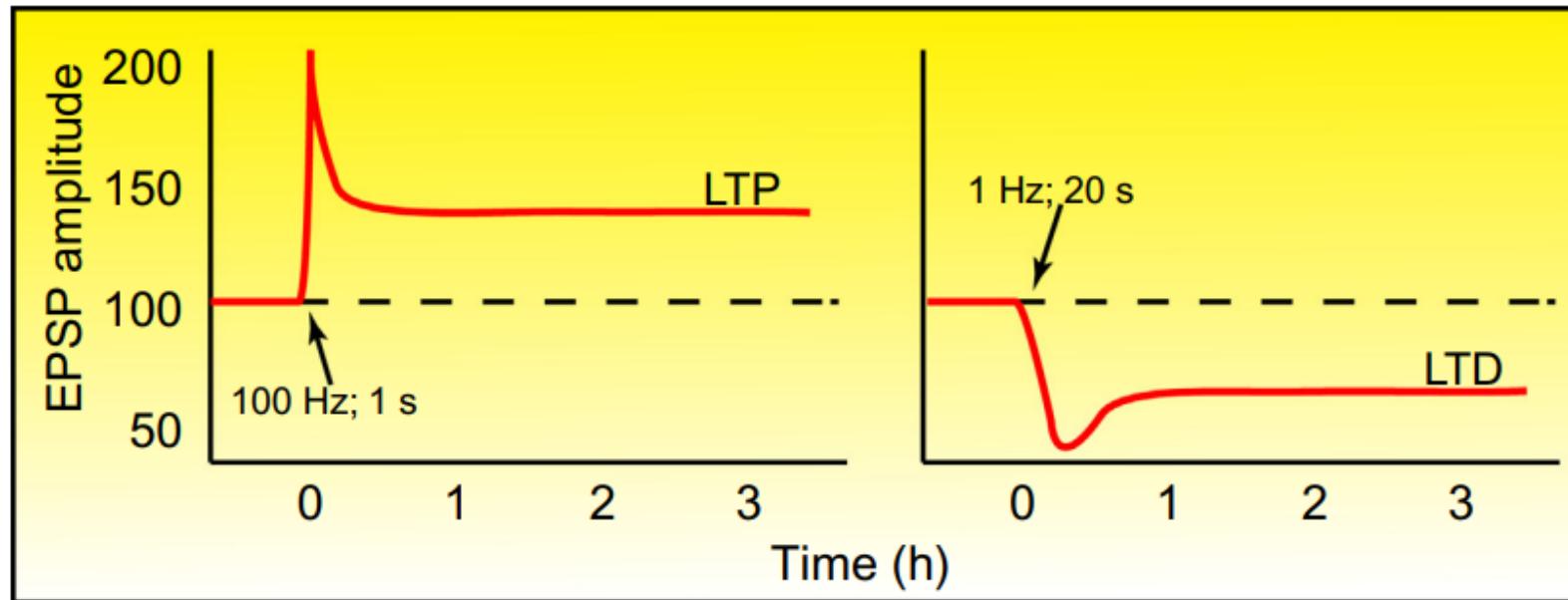


Figure: Long-term potentiation (LTP) and long-term depression (LTD).

Plots of excitatory postsynaptic potential amplitude at a hippocampal synapse over time during two different stimulus patterns. (Left panel) Following a long burst of high-frequency stimulation (100 Hz for 1 s), synapses strengthen, leading to a larger EPSP amplitude, and this is maintained for hours (LTP). The transient spike in strengthening that occurs immediately after the 100 Hz stimulus train results from post-tetanic potentiation. (Right panel) Following a low-frequency train of activity (1 Hz for 20 s), synapses weaken persistently, leading to a smaller EPSP amplitude (LTD).

Image from: Meriney, Stephen D. (2019). *Synaptic Transmission // Synaptic Plasticity.*, (), 287–329.

Synaptic plasticity: Adapting the connections

- **Spike timing dependent plasticity (STDP):**
 - The relative timing of input and output spikes determines the polarity of synaptic change.
 - The timing between presynaptic and postsynaptic spikes
 - Can determine whether the change in synaptic strength is positive or negative
 - ***Hebbian STDP:*** If the presynaptic spike occurs slightly before the postsynaptic spike (e.g., 1–40 ms before), the synapse is strengthened, whereas if the presynaptic spike occurs slightly after (e.g., 1–40 ms after), the synaptic strength is decreased.

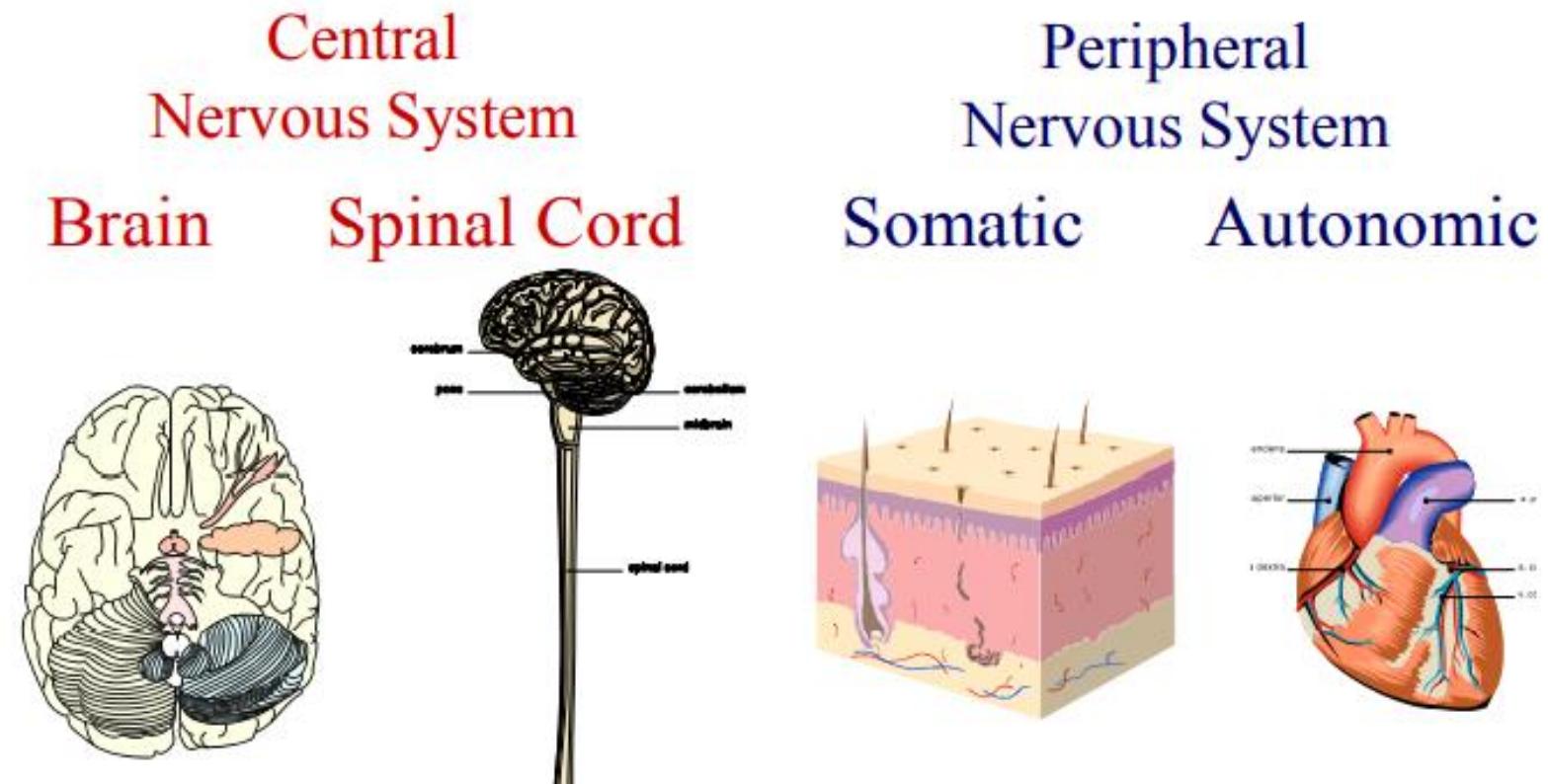
Synaptic plasticity: Adapting the connections

- Short-term facilitation/depression
 - The plasticity is rapid but not long-lasting.
- Short-term depression: The effect of each successive spike in an input spike train (sequence of spikes) is diminished compared to the preceding spike.
- Short-term facilitation: The effect of each successive spike has a larger effect than its predecessor, until a saturation point is reached

Brain Organization, Anatomy, and Function

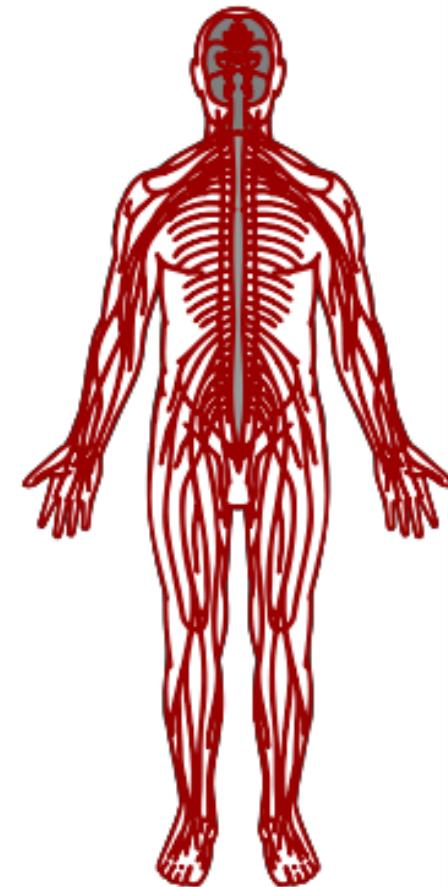
- The design of a brain-computer interface typically involves choices regarding which brain areas to record from and, in some cases, which brain areas to stimulate.
- The human nervous system can be broadly divided into
 - The central nervous system (CNS).
 - The CNS consists of the brain and the spinal cord.
 - The peripheral nervous system (PNS).
 - The PNS consists of the somatic nervous system (neurons connected to skeletal muscles, skin, and sense organs) and the autonomic nervous system (neurons that control visceral functions such as the pumping of the heart, breathing, etc.).

Brain Organization, Anatomy, and Function



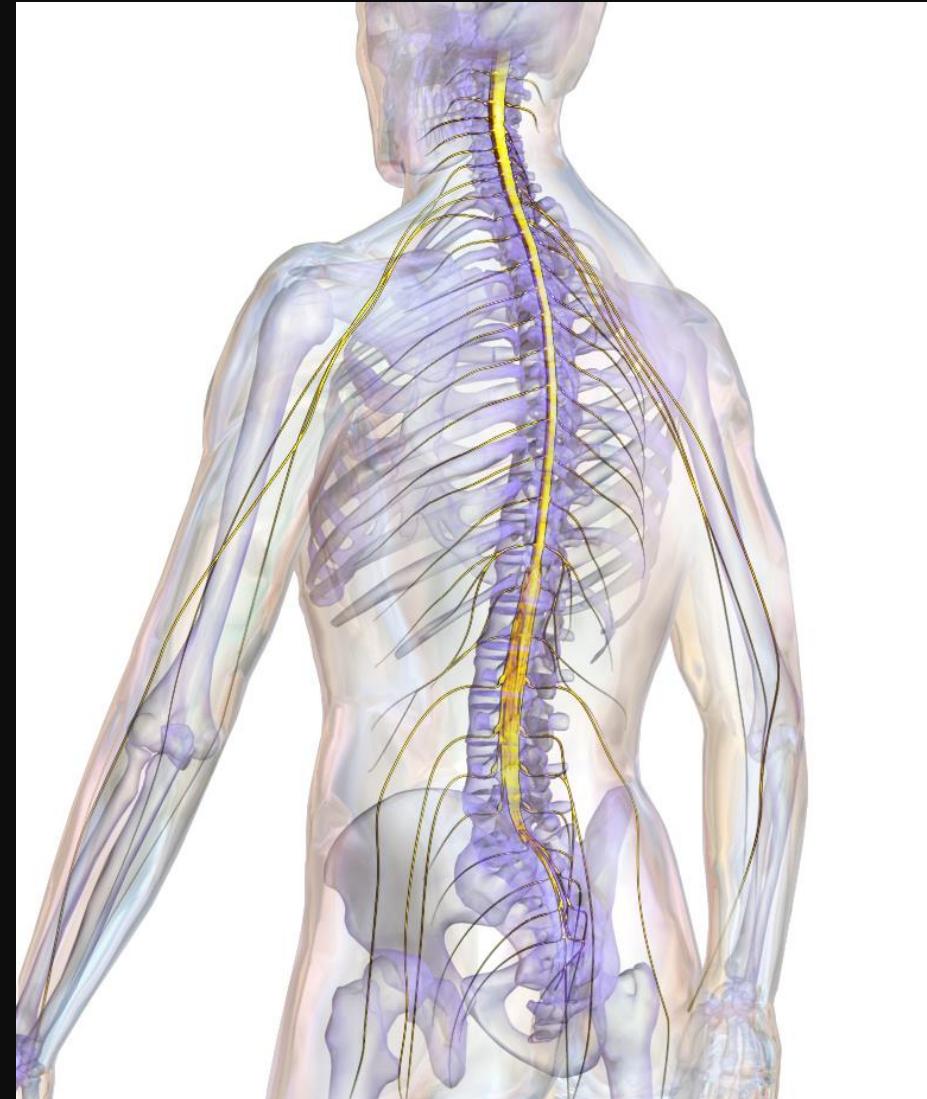
Skeletal/Somatic Nervous System

- Nerves that connect to voluntary skeletal muscles and to sensory receptors
- Afferent Nerve Fibers (incoming)
 - Axons that carry info away from the periphery to the CNS
- Efferent Nerve Fibers (outgoing)
 - Axons that carry info from the CNS outward to the periphery



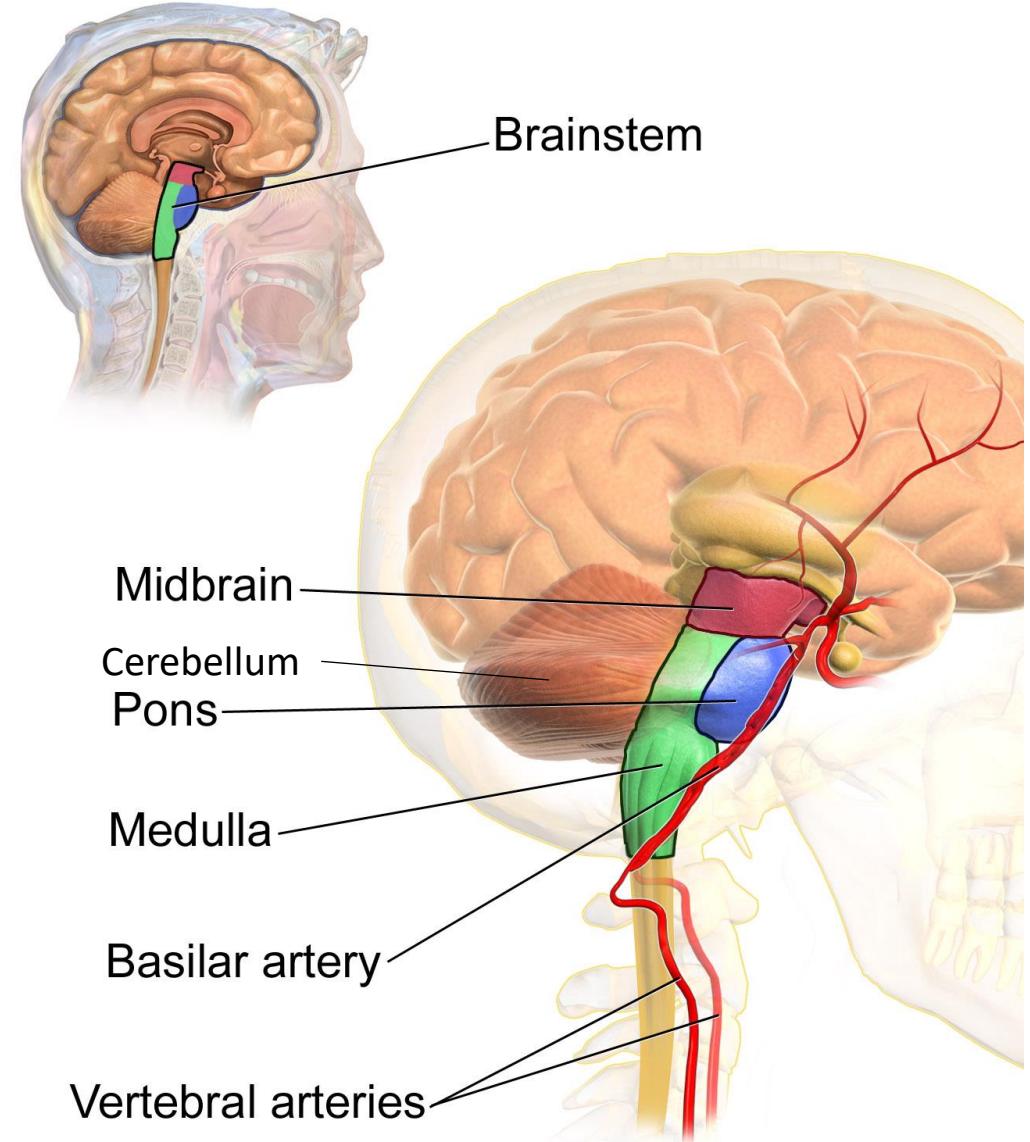
Autonomic and Central Nervous System

- Autonomic: Nerves that connect to the heart, blood vessels, smooth muscles, and glands
- CNS = Brain + Spinal Cord
- Spinal Cord
 - Local feedback loops control reflexes
 - Descending motor control signals from the brain activate spinal motor neurons
 - Ascending sensory axons transmit sensory feedback information from muscles and skin back to brain



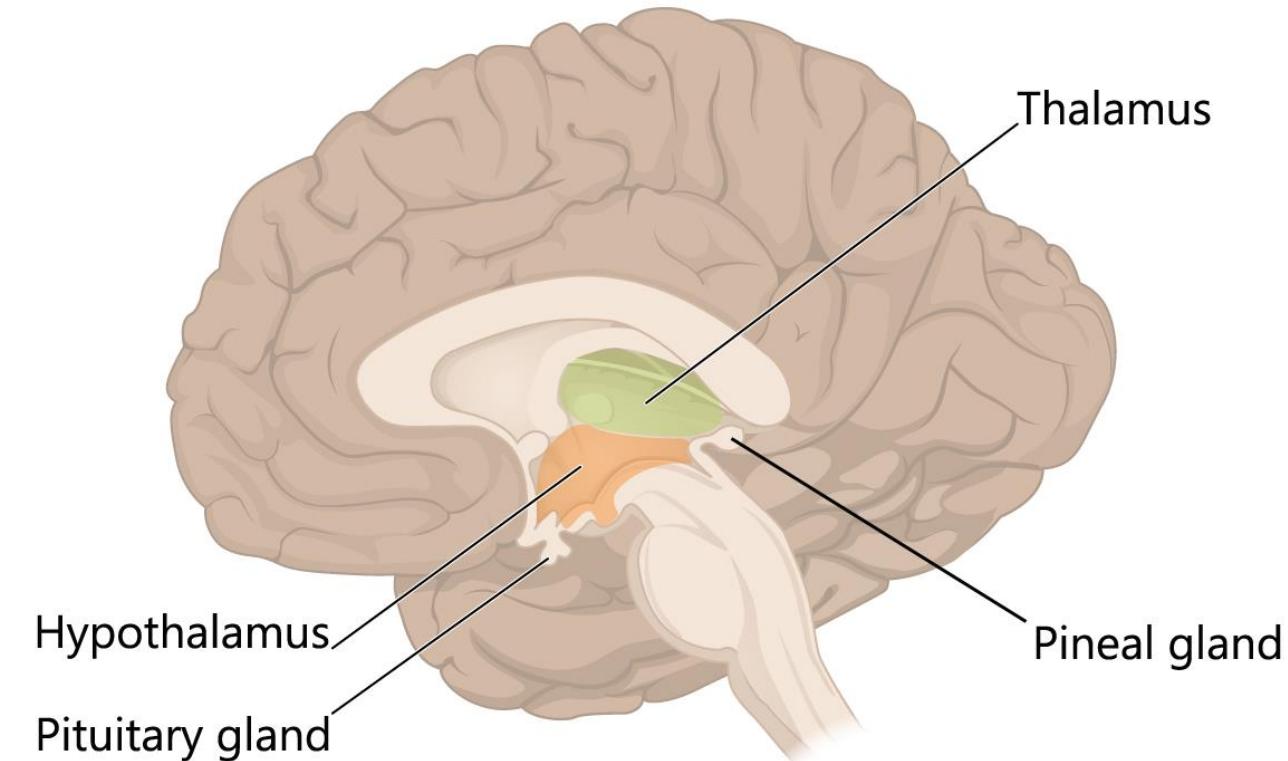
Major Brain Regions: Brain Stem

- Medulla: Breathing, muscle tone and blood pressure
- Pons: Connects brainstem with cerebellum & involved in sleep and arousal
- Cerebellum: Coordination of voluntary movements and sense of equilibrium
- Midbrain: Eye movements, visual and auditory reflexes



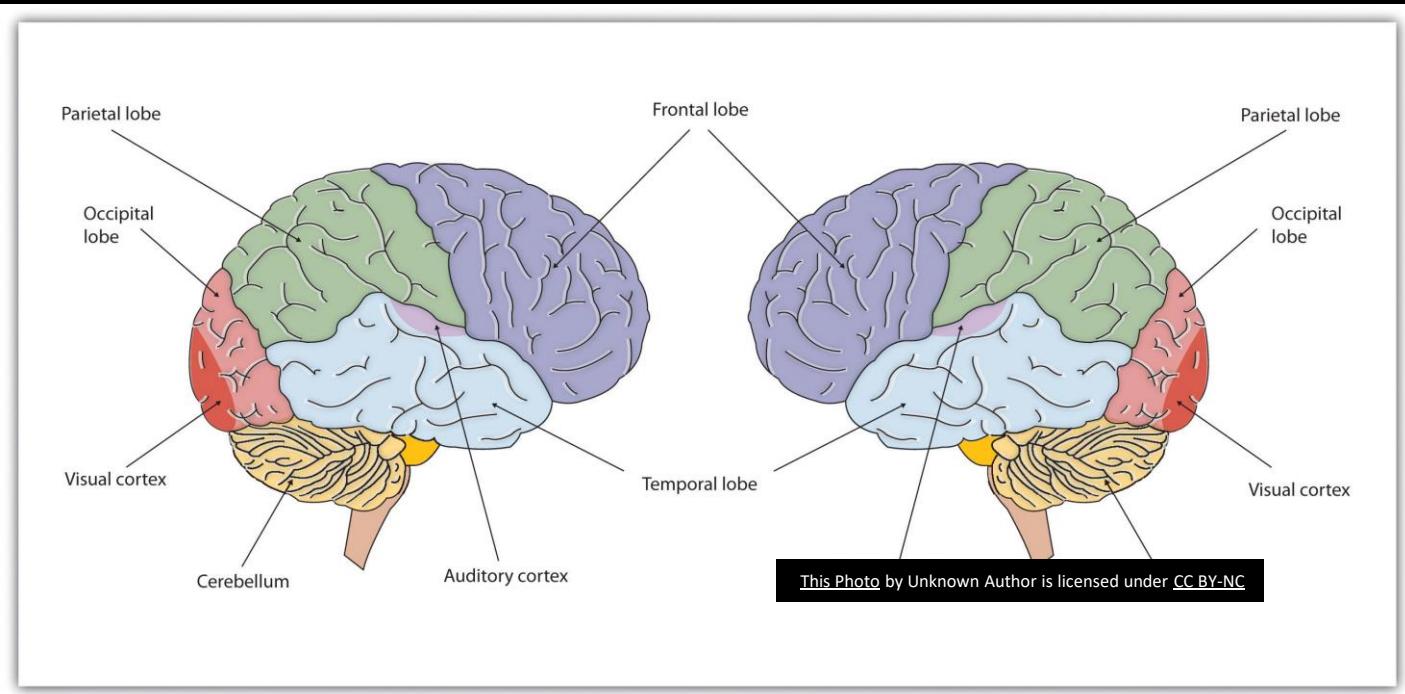
Major Brain Regions: Diencephalon

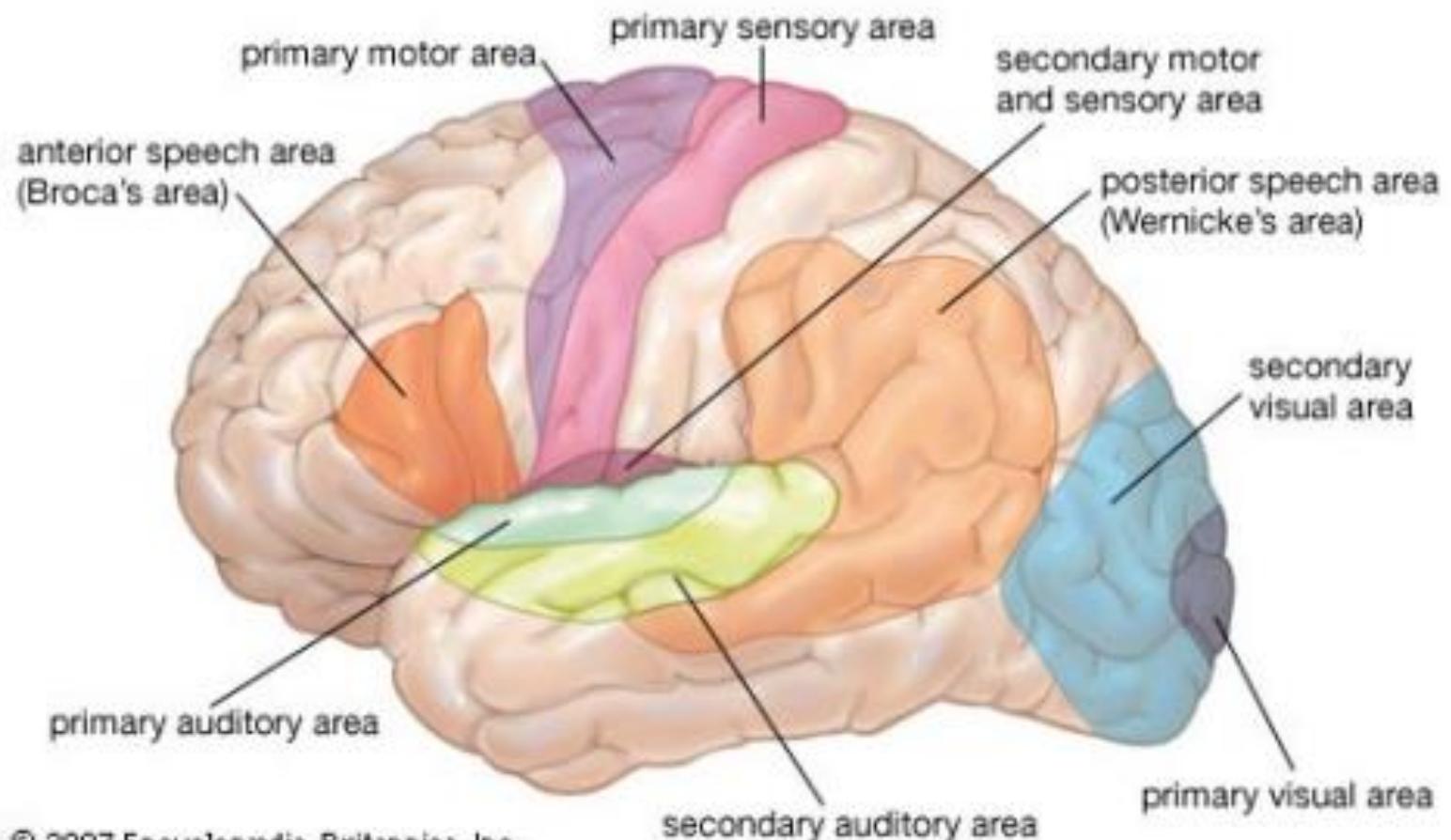
-
- Thalamus: Relay station for all sensory info (except smell) to the cortex
 - Hypothalamus Regulates basic needs fighting, fleeing, feeding, and mating



Major Brain Regions: Cerebral Hemispheres

- Consists of Cerebral cortex, basal ganglia, hippocampus, and amygdala
- Involved in perception and motor control, cognitive functions, emotion, memory, and learning





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Figure 2.2: Regions of the cerebral cortex [Goldberg, 2002]

Cortical area	Function
Auditory association area	Complex processing of auditory information
Auditory cortex	Detection of sound quality (loudness, tone)
Broca's area (speech center)	Speech production and articulation
Prefrontal cortex	Problem solving, emotion, complex thought
Premotor cortex	Coordination of complex movement
Primary Motor cortex	Initiation of voluntary movement
Primary somatosensory cortex	Receives tactile information from the body
Sensory association area	Processing of multisensory information
Gustatory area	Processing of taste information
Wernicke's area	Language comprehension
Primary Visual Cortex	Complex processing of visual information



Brain Signal Acquisition

Course S2022

Faculty: Dr Annushree Bablani

Background

- ❖ The brain communicates using spikes-- produced when the neuron receives enough input current from other neurons via synaptic connections.
- ❖ Recording brain activity are based on detecting changes in electrical potentials in neurons
 - ❖ invasive techniques based on implanting electrodes
- ❖ Or on detecting changes in large populations of neurons
 - ❖ noninvasive techniques such as electroencephalography or EEG

Recording signals from brain

Invasive Approaches:

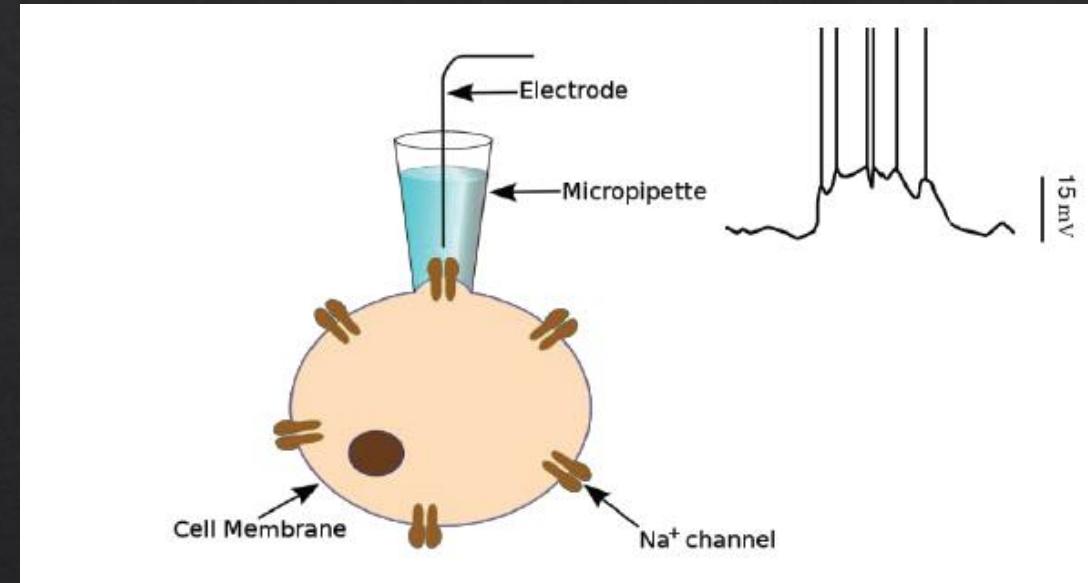
- ❖ Techniques that allow recording from individual neurons in the brain are typically invasive.
- ❖ They involve some form of surgery,
 - ❖ A part of the skull is removed, an electrode or implant placed in the brain, and the removed part of the skull then replaced.
- ❖ A major advantage of invasive recordings is that they allow recording of action potentials at the millisecond timescale.

Invasive Approaches

- ❖ Microelectrodes:
- ❖ A *microelectrode* is simply a very **fine wire** or other **electrical conductor** used to make contact with brain tissue.
- ❖ A typical electrode is made of **tungsten or platinum- iridium alloy** and is insulated except at the tip, which measures around $1\mu\text{m}$ in diameter (A neuron's cell body diameter is in the range of tens of μm).

Invasive Approaches

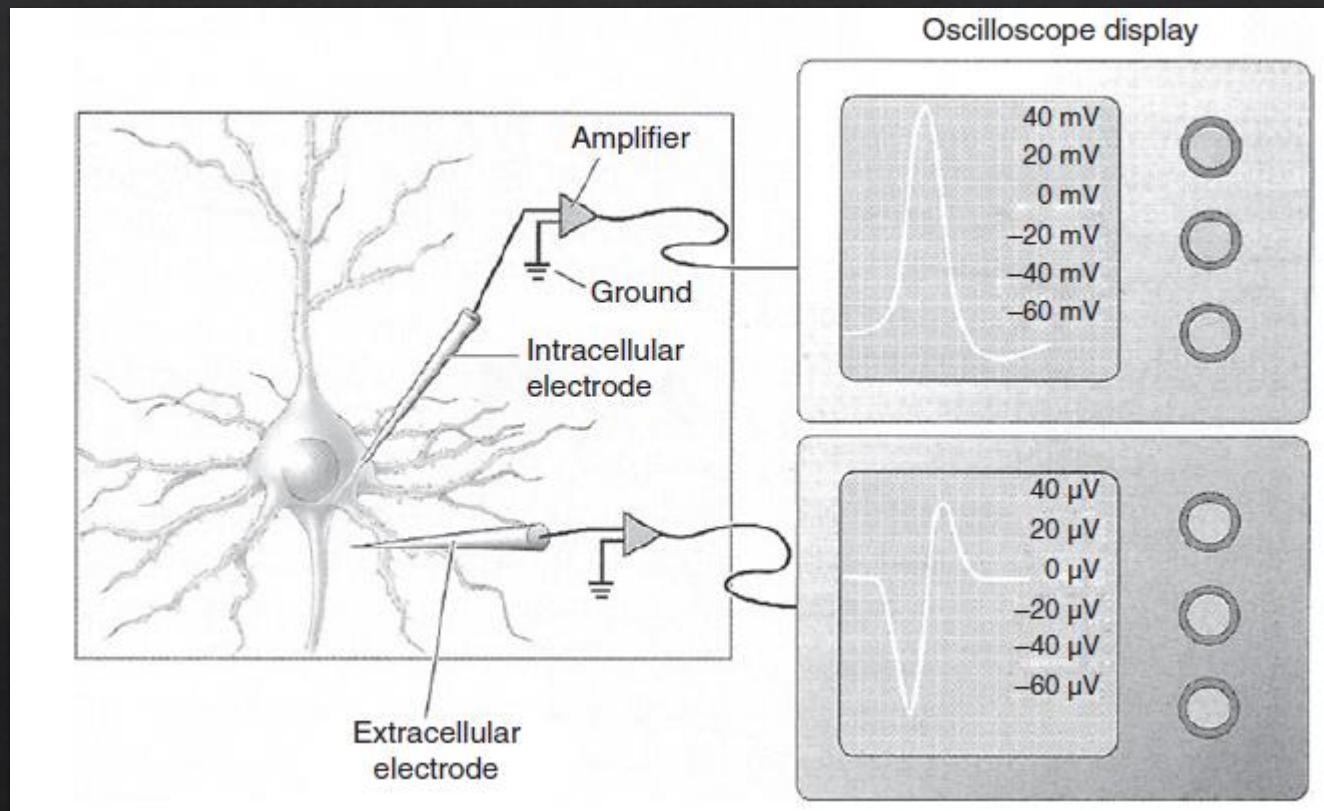
- ❖ Intracellular Recording:
- ❖ Measures the voltage or current **across the membrane of the neuron.**
- ❖ The most common technique, known as *patch clamp recording*.
- ❖ Very Delicate → Intracellular recordings are typically performed only on **slices of brain tissue**



Invasive Approaches

- ❖ Extracellular Recording:
- ❖ Recording of a **single neuron** (or single“unit”): a tungsten or platinum-iridium microelectrode with a tip size of less than 10 microns is inserted into the target brain area.
- ❖ The magnitude of the recorded signal is usually less than a millivolt and thus requires the use of amplifiers to detect the signal.
- ❖ The signal from the amplifier is fed to a computer, which performs additional processing such as filtering noise and isolating the spikes (action potentials).

Invasive Approaches



(from Bear et al., 2007).

Invasive Approaches

- ❖ When the neuron produces a spike, **positive ions flow away** from the extracellular electrode into the neuron, causing the **initial negative deflection** in the display. This is **followed by a positive deflection** as the action potential decreases and **positive charges flow out** of the neuron toward the extracellular electrode.

Invasive Approaches

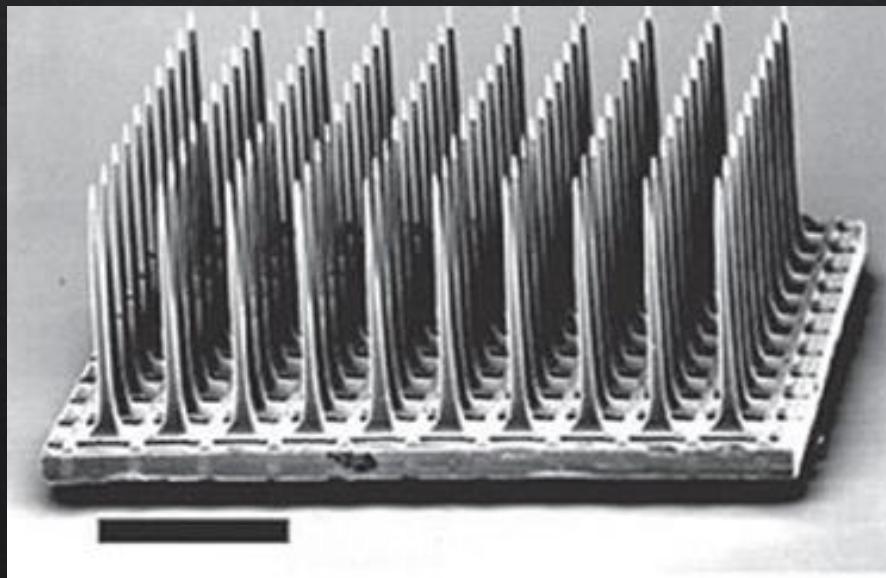
Tetrodes and Multi-Unit Recording:

- ❖ To record from **multiple neurons simultaneously** by using more than one electrode.
- ❖ **Four wires** are tightly wound together in a bundle.

Invasive Approaches

Multielectrode Arrays:

- ❖ To record from larger numbers of neurons, microelectrodes can be arranged in a **grid-like structure** to form a **multielectrode array** of $m \times n$ electrodes.



(adapted from Hochberg et al., 2006).

Invasive Approaches

- ❖ The most common types of implantable arrays are microwire, silicon-based, and flexible microelectrode arrays
- ❖ Increased **spatial resolution**
- ❖ The ability to record simultaneously from several dozens of neurons
- ❖ Opens the door to extracting complex types of information such as position or velocity signals that could be useful for controlling prosthetic devices.

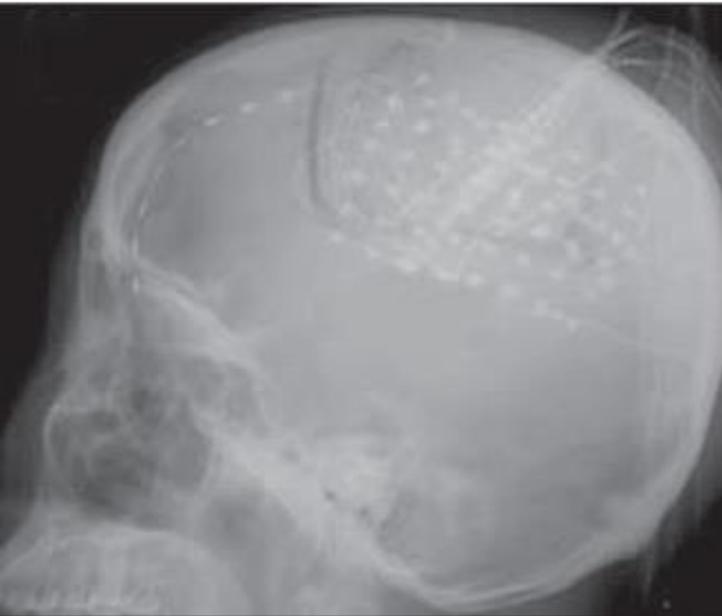
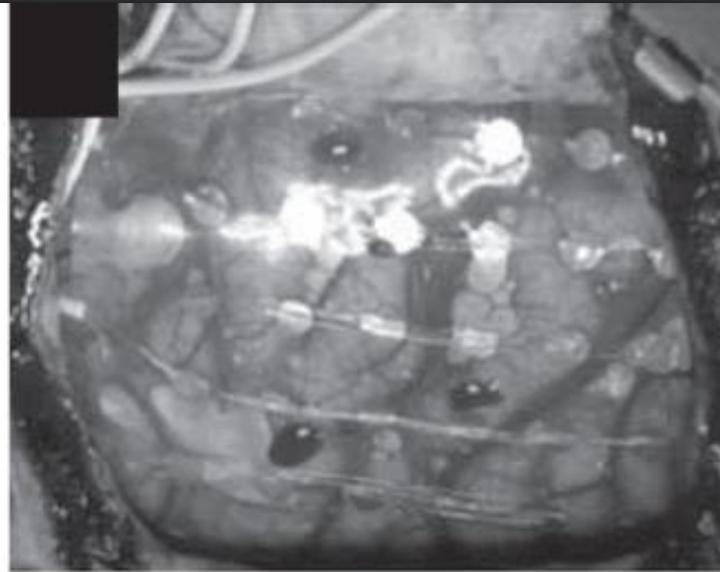
Partially Invasive Approach

Electrocorticography (ECoG):

- ❖ *Electrocorticography (ECoG)* is a technique for recording brain signals that involves **placing electrodes on the surface of the brain**.
- ❖ The procedure requires making a surgical incision into the skull to implant the electrodes on the brain surface

Partially Invasive Approach

- ❖ ECoG electrodes can record the electrical fluctuations caused by the **coherent activity of large populations of neurons** (several tens of thousands).
- ❖ **Safer** than arrays implanted inside the brain.
- ❖ ECoG electrodes may also be **less likely to wear out** compared to brain penetrating electrodes
- ❖ ECoG offers greater **spatial resolution**



(from (Miller et al., 2007)).

Partially Invasive Approach

MicroECoG:

- ❖ One disadvantage of ECoG, is the relatively large size of ECoG electrodes
- ❖ These microelectrodes are only a fraction of a millimeter in diameter and spaced only 2–3 mm apart in a grid
- ❖ Allows detection of neural activity at a much finer resolution than traditional ECoG.
- ❖ Decoding fine movements, such as the movements of individual fingers, or even speech, without actually penetrating the brain.

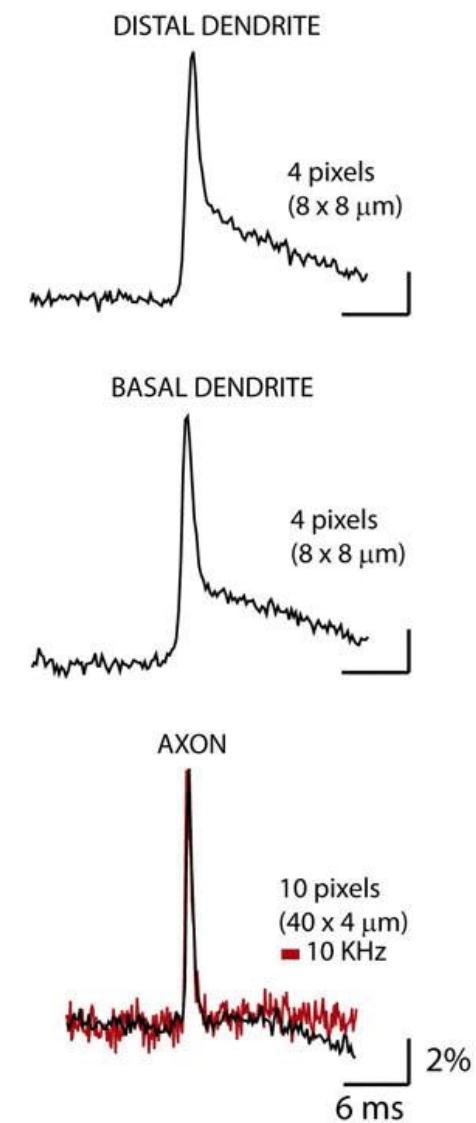
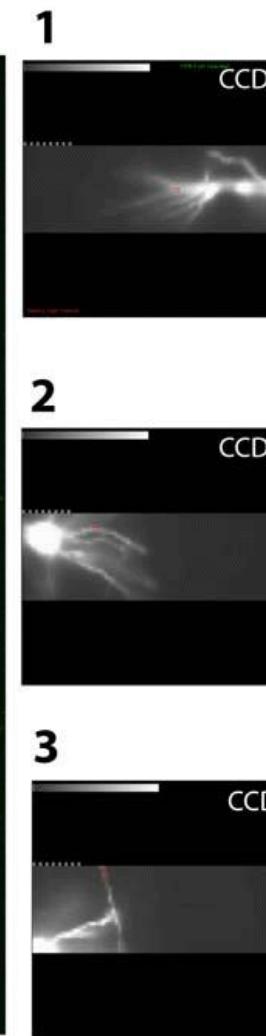
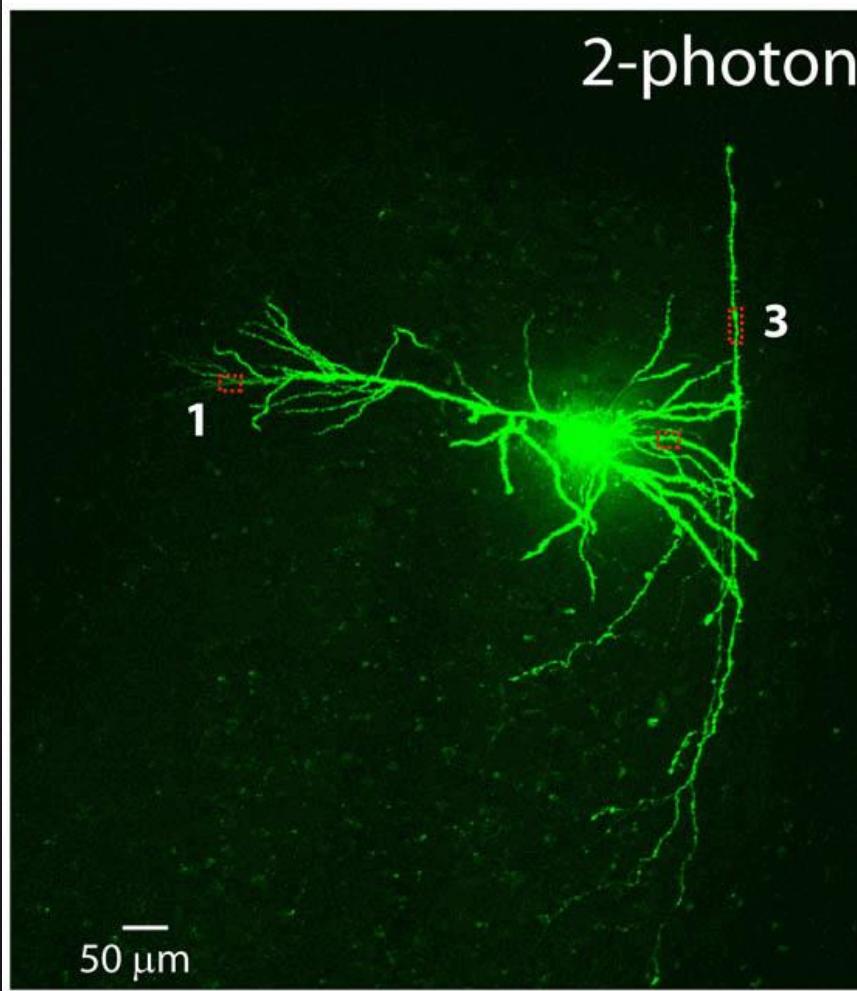
Partially Invasive Approach

Optical Recording: Voltage-Sensitive Dyes and Two-Photon Calcium Imaging:

- ❖ **Voltage-sensitive dyes**
- ❖ Neurons are stained with a voltage-sensitive dye
- ❖ Dye responds to changes in membrane potential by changing its absorption and/or fluorescence
- ❖ Recorded optical signals correspond to **summed responses** from several **simultaneously active neurons**.
- ❖ Useful for imaging macroscopic features of the brain such as feature maps in the cortex

VOLTAGE-SENSITIVE DYE IMAGING

SINGLE TRIAL RECORDINGS AT 5 KHz



(image: Scholarpedia http://www.scholarpedia.org/article/Voltage-sensitive_dye).

Partially Invasive Approach

- ❖ Two-photon calcium imaging
- ❖ Based on the fact that electrical activity in neurons is typically associated with changes in calcium concentration.
- ❖ Photon calcium imaging involves:
 - (1) using pressure ejection to load neurons with fluorescent calcium-indicator dyes
 - (2) monitoring changes in calcium fluorescence during neural activity using two-photon microscopy.

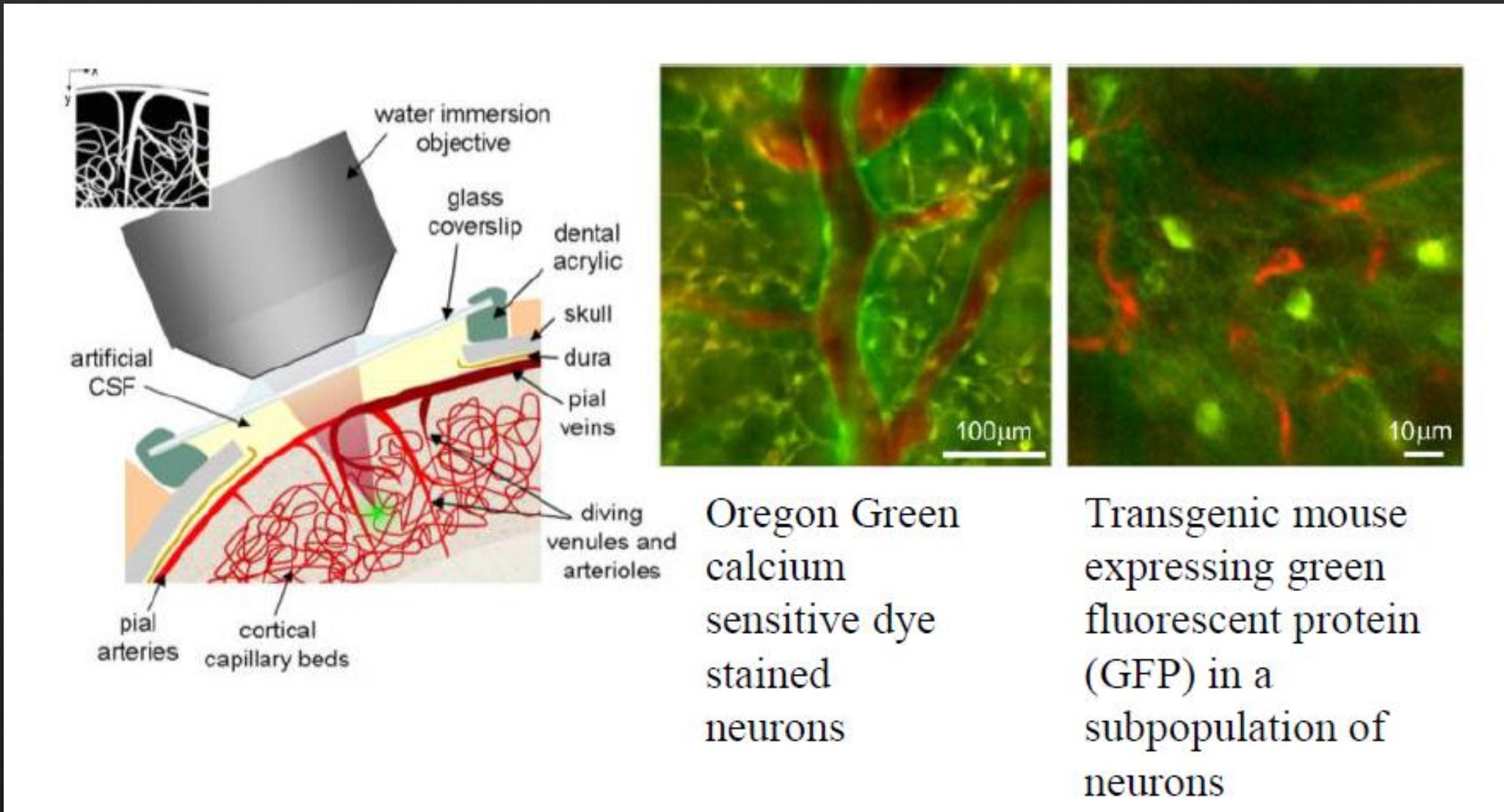


Image from Kherlopian et al., 2008).

Non Invasive Approaches

Electroencephalography (EEG)

- ❖ EEG signals reflect the summation of postsynaptic potentials from many thousands of neurons that are oriented radially to the scalp.
- ❖ EEG predominantly captures electrical activity in the cerebral cortex, whose columnar arrangement of neurons and proximity to the skull favor recording by EEG.

Non Invasive Approaches

- ❖ Electroencephalography (EEG)
- ❖ The spatial resolution is typically poor (in the square centimeter range)
 - ❖ Due to lots of muscles between the source of signal and the electrodes placed on the scalp.
- ❖ The temporal resolution is good (in the milliseconds range)

Non Invasive Approaches

- ❖ The measured signals are in the range of a few tens of microvolts, necessitating the use of powerful amplifiers and signal processing to amplify the signal and filter out noise.
- ❖ Artifacts in the EEG signal
 - ❖ eye movements, eye blinks, eyebrow movements, talking, chewing, and head movements

Non Invasive Approaches

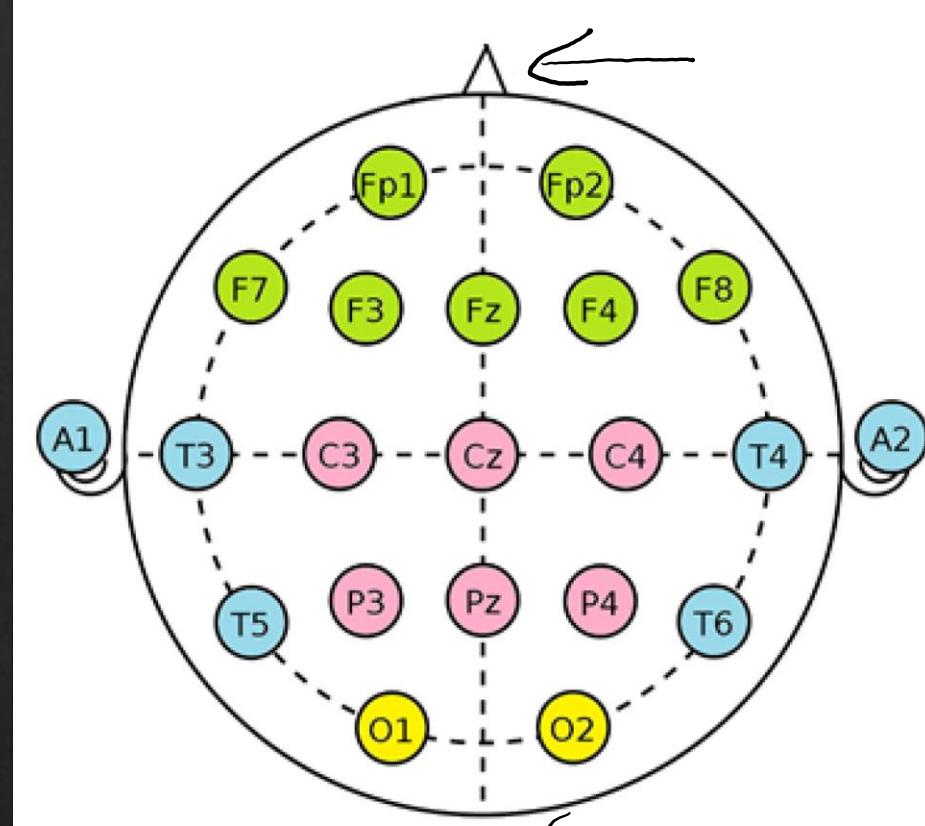
- ❖ EEG recording involves the subject wearing a cap or a net into which the recording electrodes are placed
- ❖ A conductive gel or paste is injected into the holes of the cap before placing the electrodes.



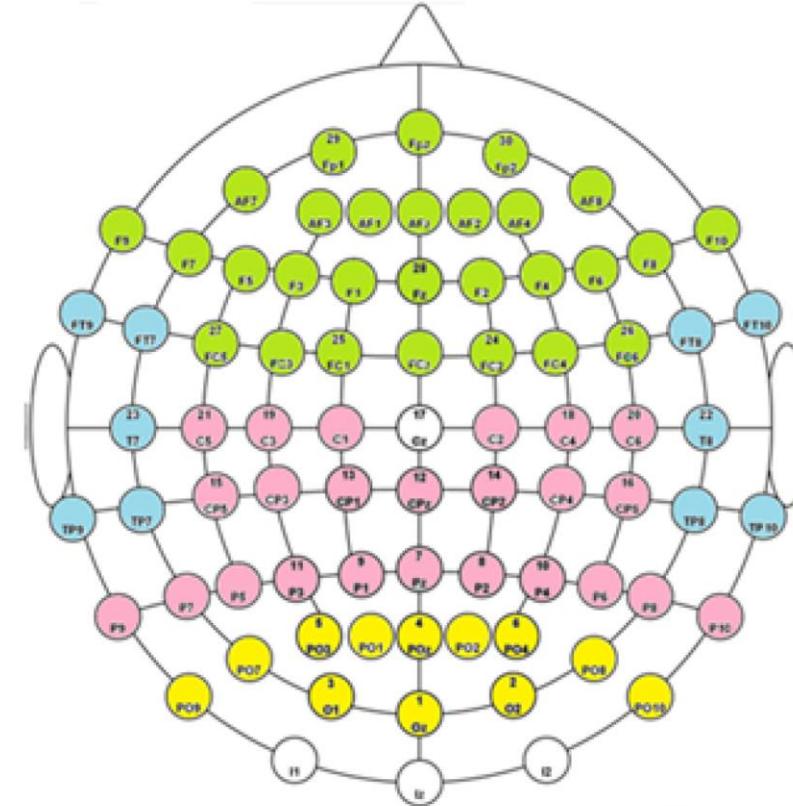
courtesy K. Miller

Non Invasive Approaches

- ❖ The international 10–20 system is a convention used to specify standardized electrode locations on the scalp.
- ❖ C = central, P = parietal, T = temporal, F = frontal, Fp = frontal polar, O = occipital, A = mastoids



10-20 Electrode System



10-10 Electrode System

Frontal Lobe

Temporal Lobe

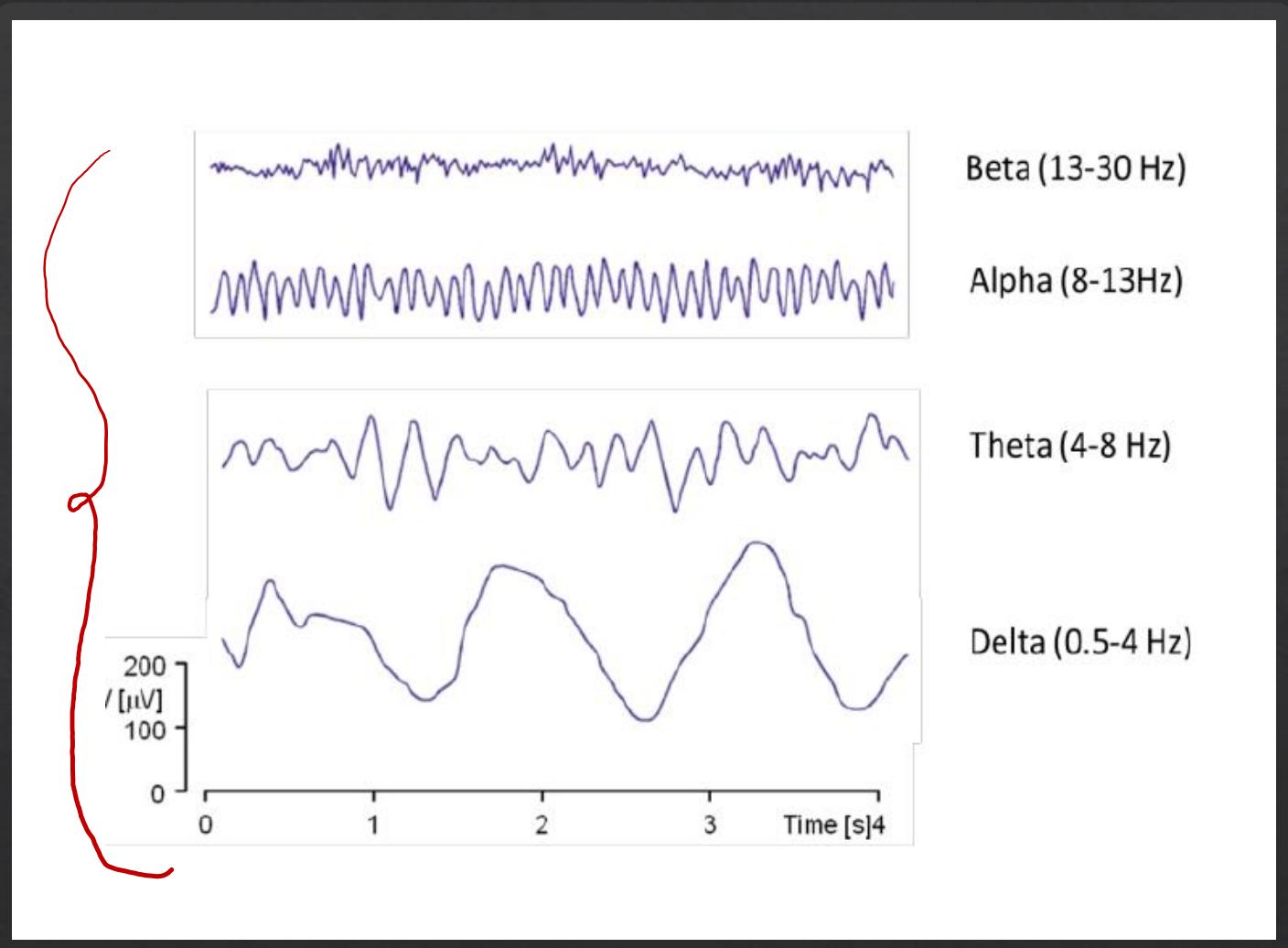
Parietal Lobe

Occipital Lobe

- ❖ The mastoids reference electrode locations behind each ear (A1 and A2).
- ❖ Other reference electrode locations are **nasion**, at the top of the nose, level with the eyes; and **inion**, at the base of the skull on the midline at the back of the head.
- ❖ In a typical setup, each EEG electrode is connected to one input of a differential amplifier, and the other input is connected to a reference electrode

- ❖ The amplification of voltage between the active electrode and the reference is typically 1,000–100,000 times.
- ❖ The amplified signal is passed through a filter and then digitized via an A/D (analog to digital) converter.
- ❖ After digitization, the EEG signal may be additionally filtered by a 1–50 Hz bandpass filter.
 - ❖ Excludes noise and movement artifacts in the very low and very high frequency ranges.

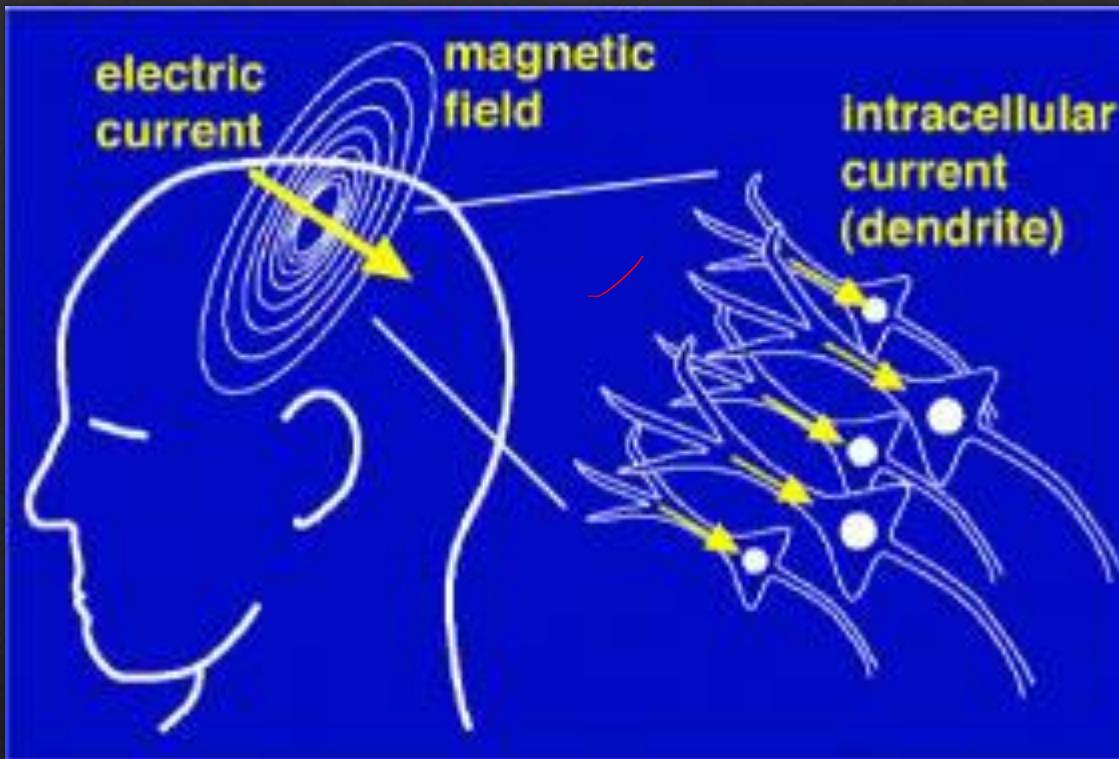
- ❖ EEG recordings are well-suited to capturing oscillatory brain activity or “brain waves” at a variety of frequencies
 - ❖ Alpha waves (8 to 13 Hz)
 - ❖ Beta waves (13 to 30 Hz)
 - ❖ Delta waves (0.5-4 Hz)
 - ❖ Theta waves (4-8 Hz)
 - ❖ Gamma waves (30-100 Hz or more)



Non Invasive Approaches

Magnetoencephalography (MEG):

- ❖ Measures **magnetic fields** produced by activity of thousands of cortical neurons oriented perpendicular to the cortical surface
- ❖ Magnetic fields not distorted by skull and scalp
- ❖ Better **spatial resolution** than EEG
- ❖ Expensive and bulky
- ❖ Magnetically shielded rooms



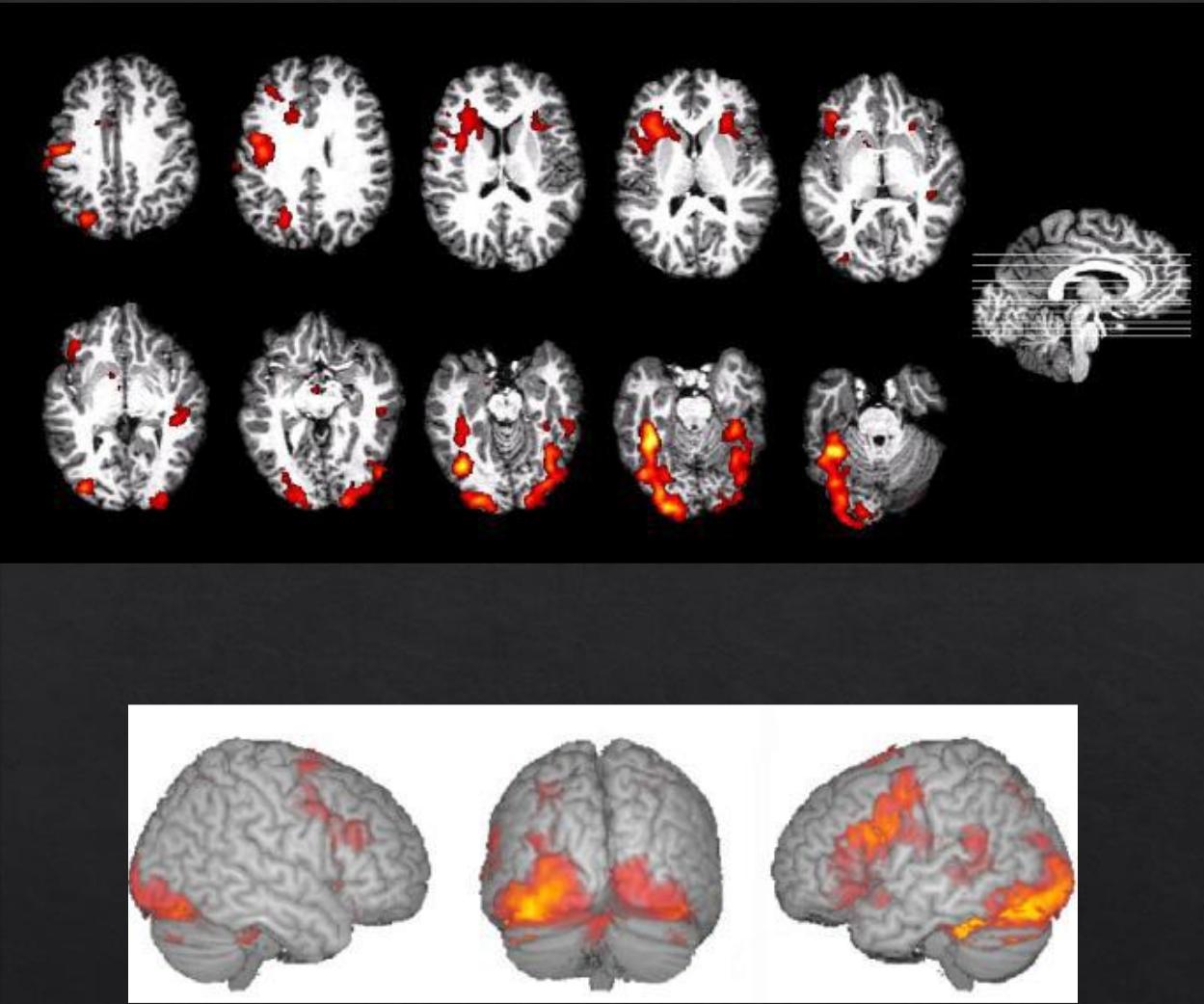
(image A: Wikimedia Commons;

image B: http://dateline.ucdavis.edu/photos_images/dateline_images/040309/DondersMEGOle_W2.jpg).

Non Invasive Approaches

Functional Magnetic Resonance Imaging (fMRI) :

- ❖ Measures **changes in blood flow** due to increased activation of neurons in an area
- ❖ Relies on paramagnetic properties of oxygenated and deoxygenated hemoglobin in the blood
- ❖ Produces images showing **blood-oxygenation-level-dependent** signal changes (BOLD)

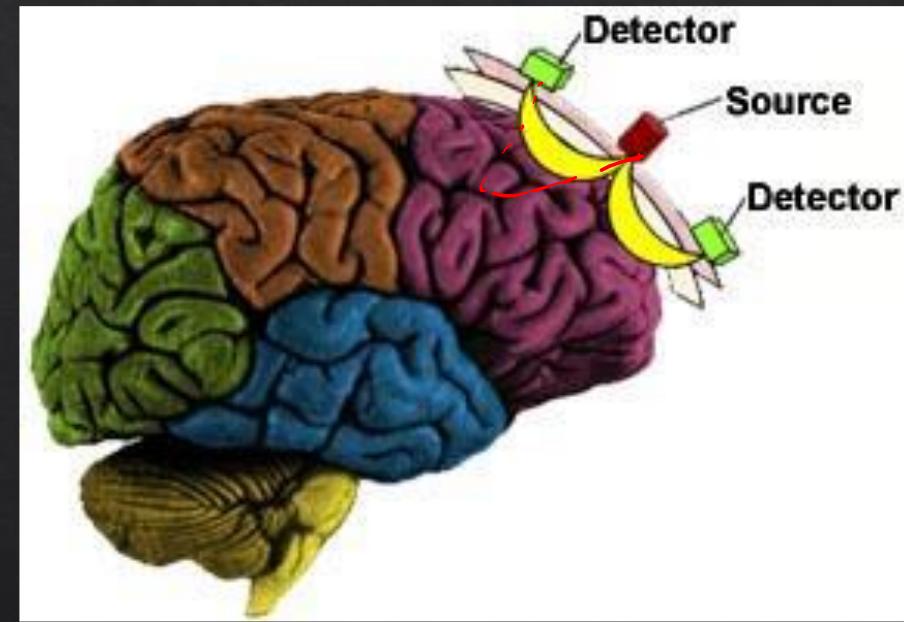
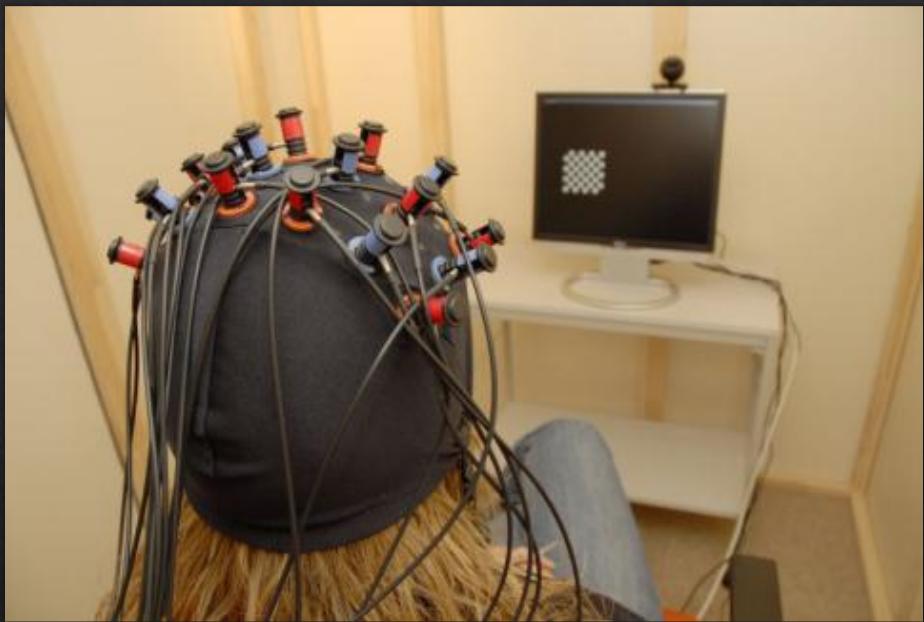


Example fMRI Images (word reading task)

Non Invasive Approaches

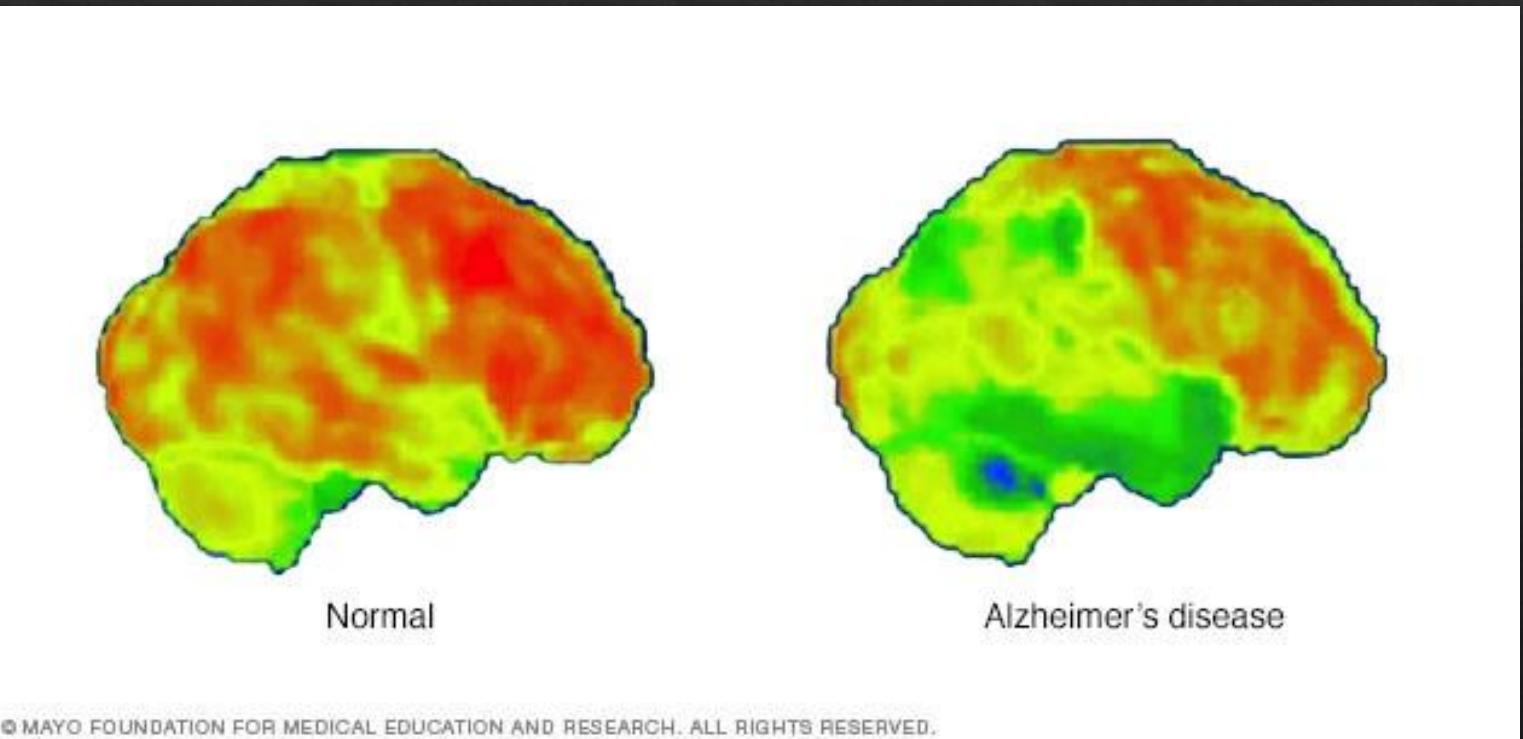
Functional Near-Infrared Spectroscopy (fNIR)

- ❖ Measures change in blood oxygenation level caused by increased neural activity in the brain.
- ❖ Based on detecting **near-infrared light absorbance** of hemoglobin in the blood with and without oxygen.
- ❖ Maps neural activity using “*optodes*”(emitters and detectors)



Non-Invasive Approaches

- ❖ **Positron Emission Tomography (PET):**
- ❖ Measures emissions **from radioactively labeled, metabolically active chemicals** that have been injected into the bloodstream for transportation to the brain.
 - ❖ The labeled compound is called a *radiotracer*.
- ❖ Sensors in the PET scanner detect the radioactive compound
 - ❖ As a result of metabolic activity caused by brain activity.
- ❖ Generate two-or three-dimensional images indicating the amount of brain activity.

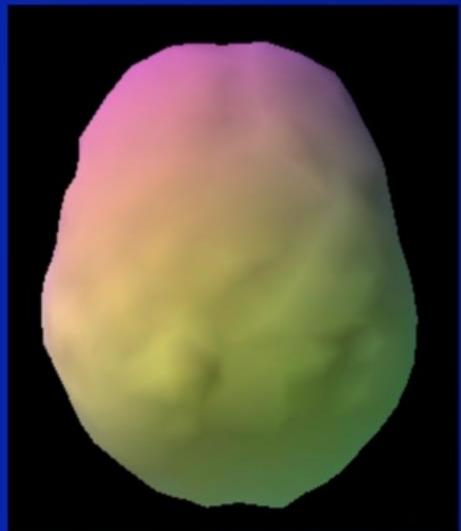


A PET scan can compare a normal brain (left) with one affected by Alzheimer's disease (right). An increase in blue and green colors shows decreased brain metabolic activity due to Alzheimer's disease.

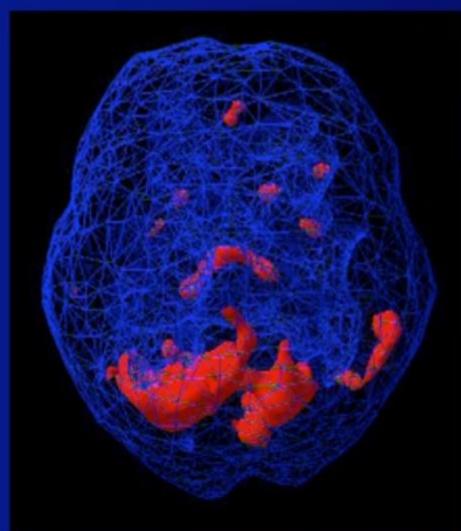
Non Invasive Approaches

- ❖ Single-photon emission-computed tomography (**SPECT**):
- ❖ SPECT is a nuclear medicine technique that uses **gamma rays** to study the brain.
- ❖ A **radioactive substance** is injected into the patient's body and is scanned using a SPECT machine.
- ❖ Allows doctors to see **how blood flows** into tissues and organs.
 - ❖ Active, inactive, or overactive.
- ❖ Averages the brain activity over a few minutes and generates an image.

Healthy Brain SPECT Scans

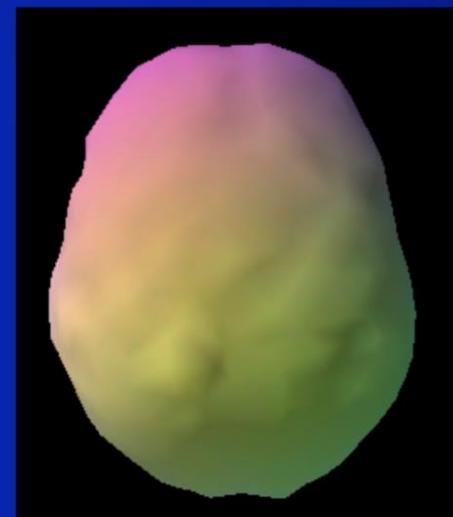


Surface View

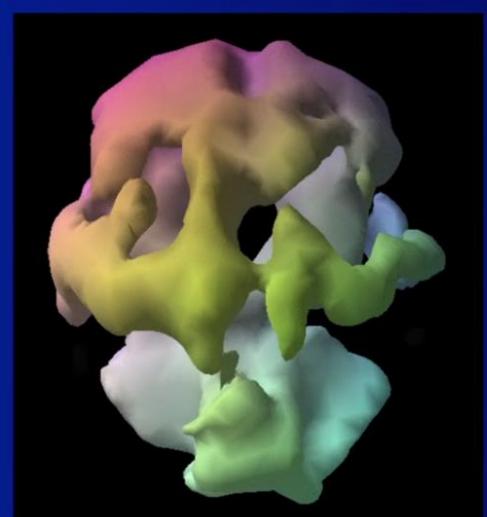


Active View

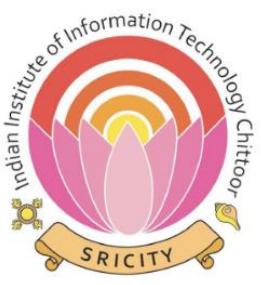
Healthy vs Alzheimer's Disease



Healthy



Alzheimer's



EEG Measure

Course Instructor

Dr. Annushree Bablani

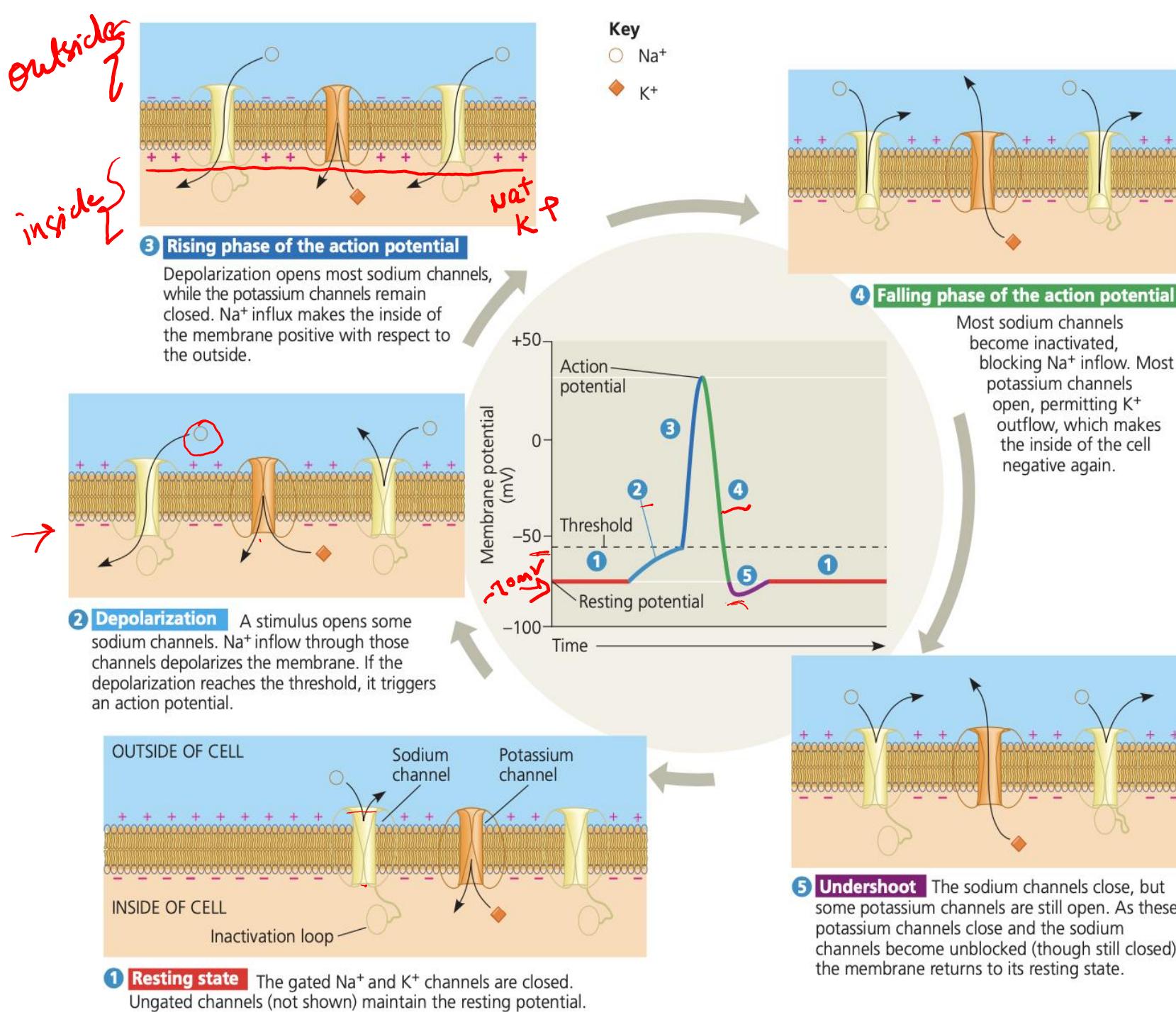
Acknowledgments: Dr Sreeja SR

REVISIT

- **Neurons** are nerve cells that transfer information within the body
- Neurons use two types of signals to communicate: electrical signals (long-distance) and chemical signals (short-distance)
- Nervous systems process information in three stages: sensory input, integration, and motor output

Hyperpolarization and Depolarization

- Changes in membrane potential occur because neurons contain **gated ion channels** that open or close in response to stimuli.
- When gated K⁺ channels open, K⁺ diffuses out, making the inside of the cell more negative. This is **hyperpolarization**, a reduction in magnitude of the membrane potential.
- Opening other types of ion channels triggers a depolarization, an increase in the magnitude of the membrane potential. For example, depolarization occurs if gated Na⁺ channels open and Na⁺ diffuses into the cell.
- **Graded potentials** are changes in polarization where the magnitude of the change varies with the strength of the stimulus.
- If a depolarization shifts the membrane potential sufficiently, it results in a massive change in membrane voltage called an **action potential**.



Generation of Postsynaptic Potentials

- Direct synaptic transmission involves binding of neurotransmitters to **ligand-gated ion channels** in the postsynaptic cell.
- Neurotransmitter binding causes ion channels to open, generating a postsynaptic potential.
- Postsynaptic potentials fall into two categories
 - **Excitatory postsynaptic potentials (EPSPs)** are depolarizations that bring the membrane potential toward threshold.
 - **Inhibitory postsynaptic potentials (IPSPs)** are hyperpolarizations that move the membrane potential farther from threshold.

What are we measuring with EEG?

What does the EEG record?

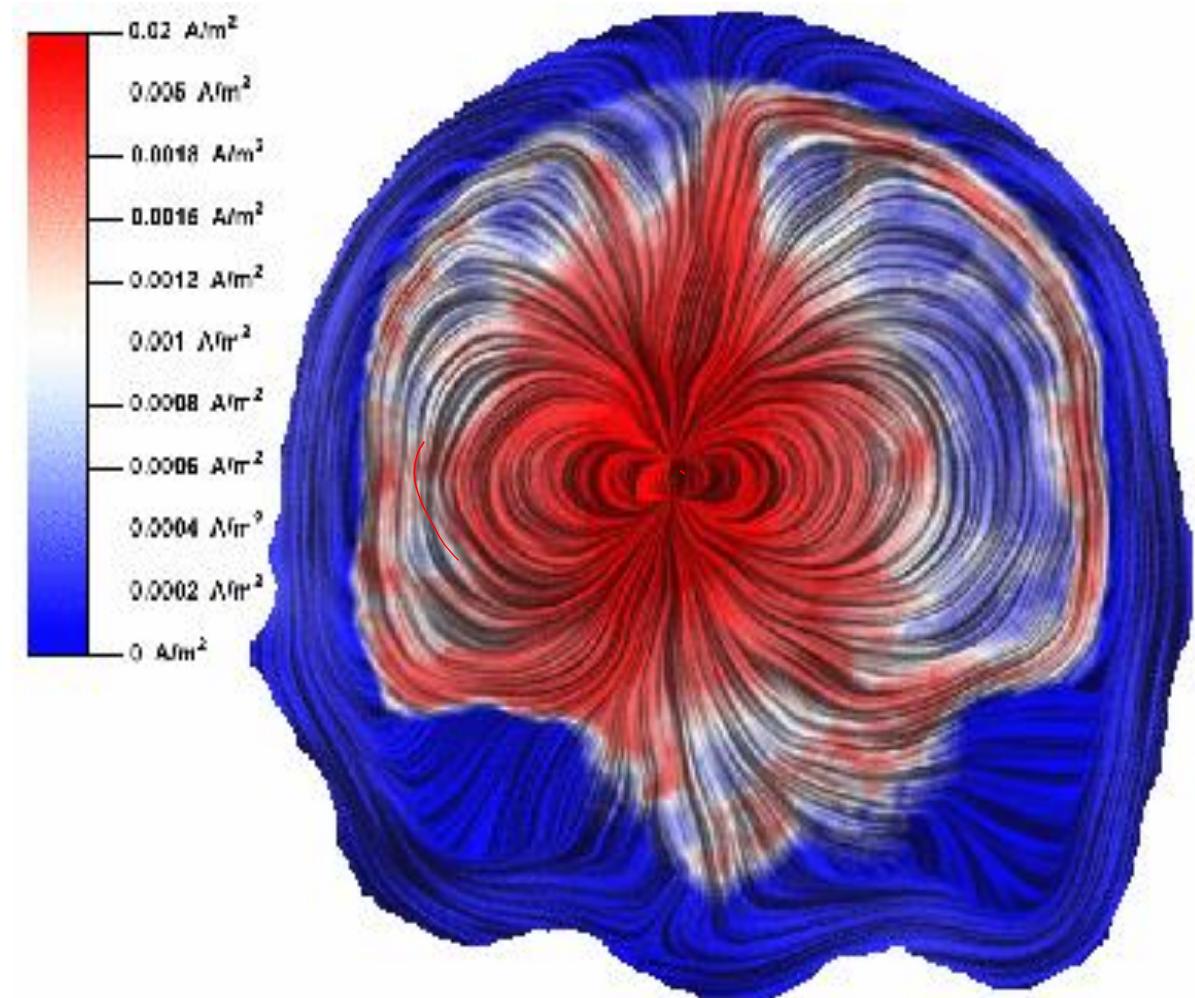
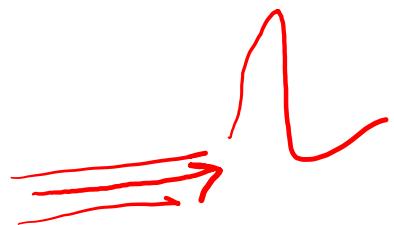
Mainly NOISE!!

Volume Conduction

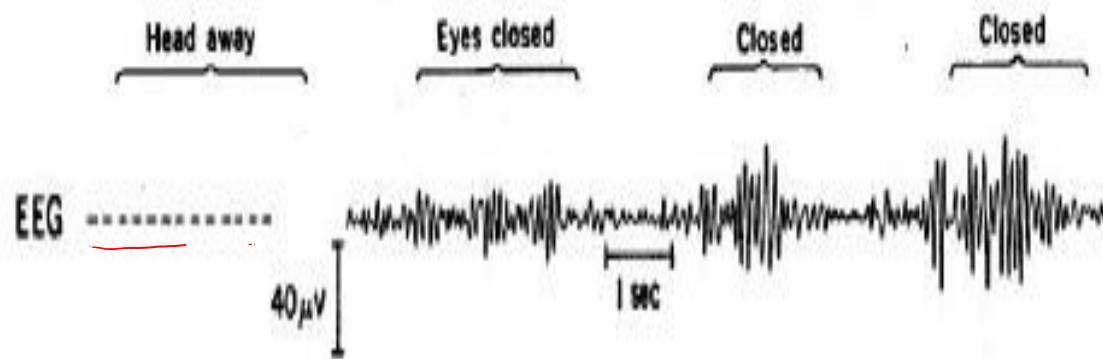
EEG directly measures the neural activity.

What kind of neuronal activity?

- Action potentials
- Postsynaptic potentials

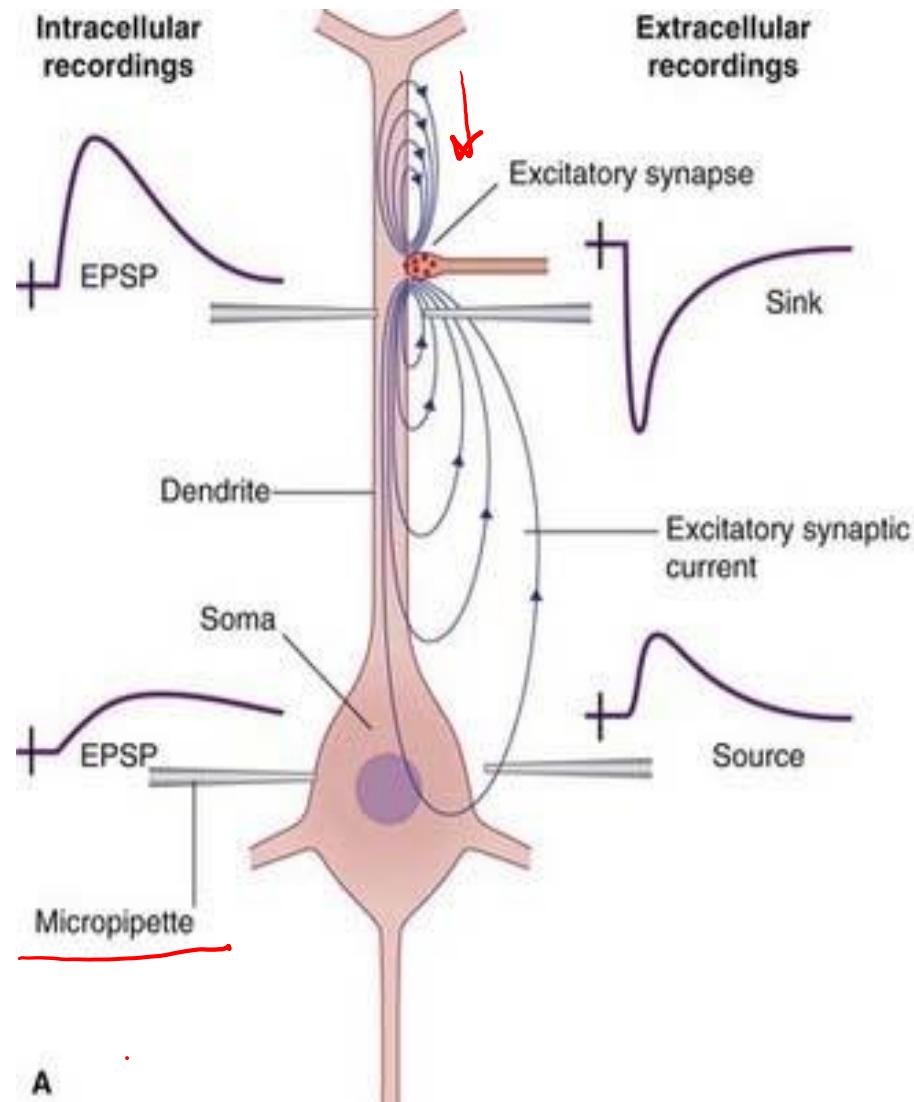


EEG measures the underlying neural currents



- **EEG:** Measures differences in electric potential at the scalp.
- Non-invasive, cover the whole head, and have very high temporal resolution.

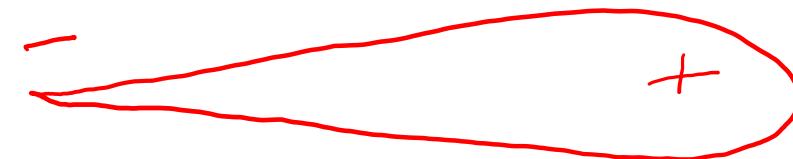
Neural basis of the EEG



When an EPSP is generated in the dendrites of a neuron an extracellular electrode detects a negative voltage difference, resulting from Na⁺ currents flowing inside the neuron's cytoplasm.

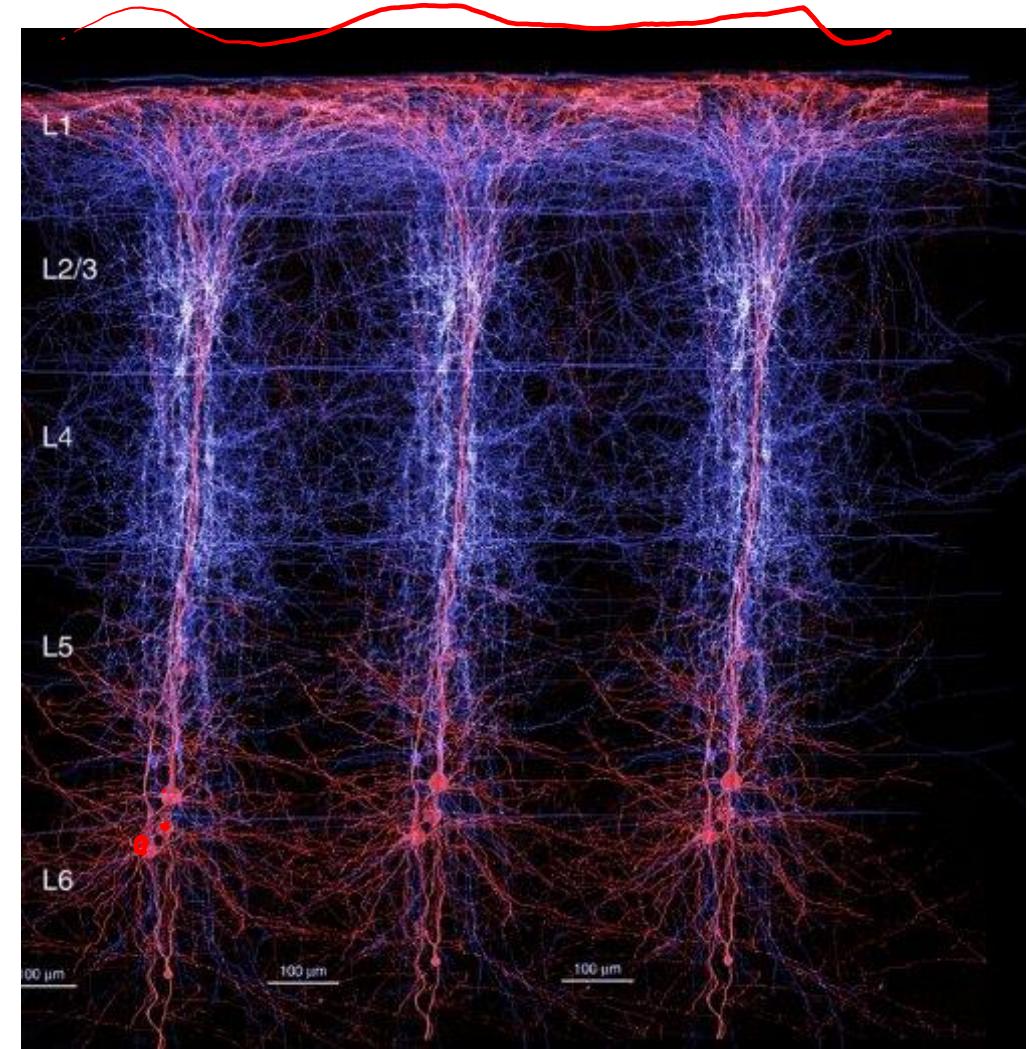
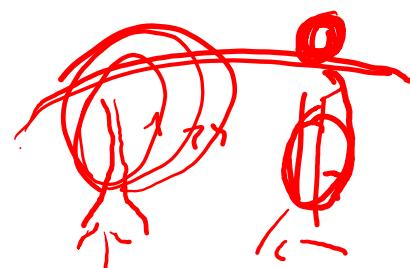
The current completes a loop further away the excitatory input (Na⁺ flows outside the cell), being recorded as a positive voltage difference by an extracellular electrode.

This process can last hundreds of milliseconds.

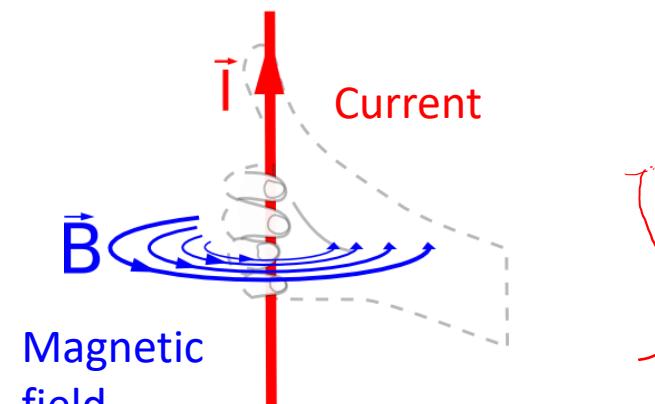
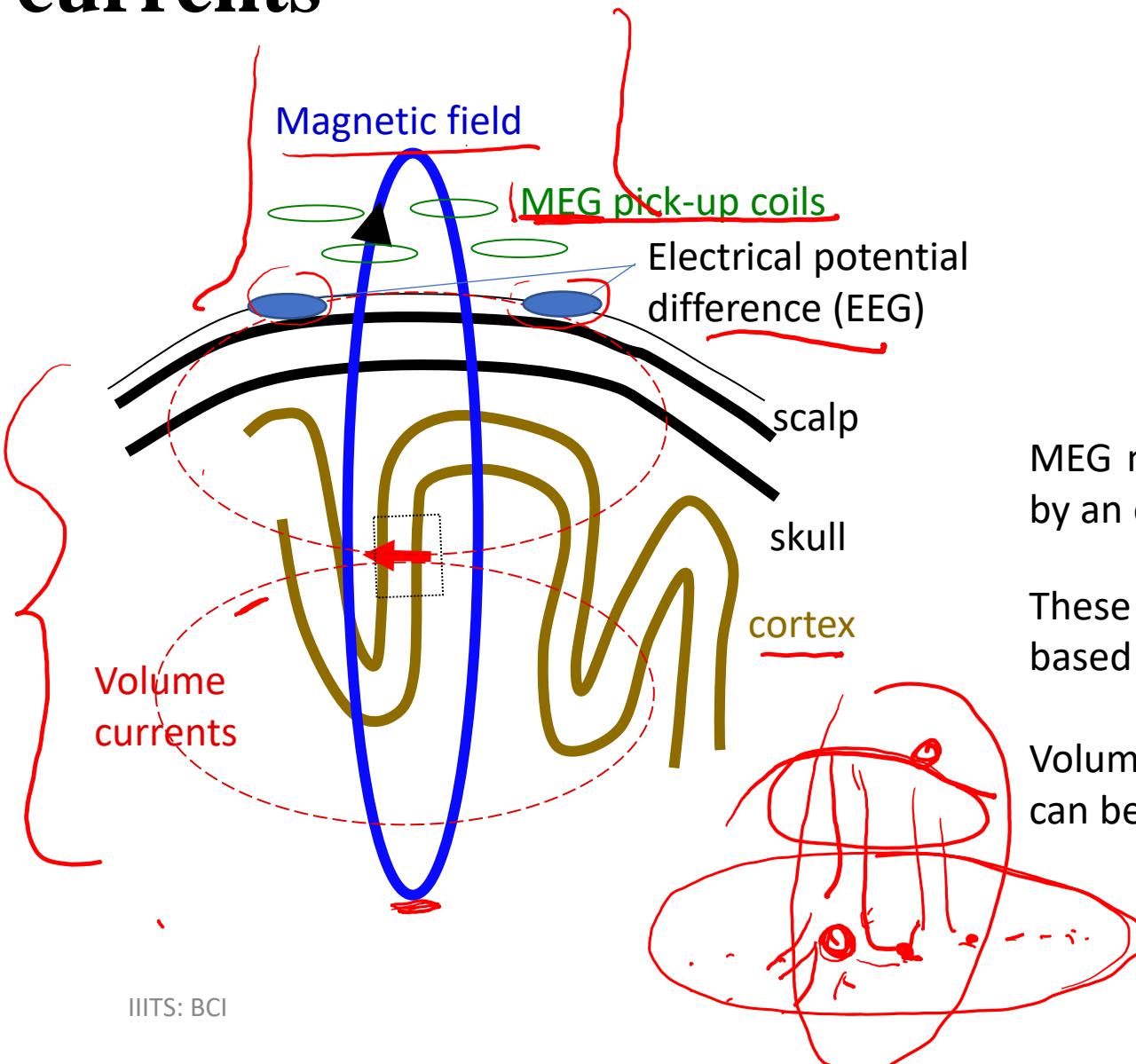


From single neuron to neural population

- The geometry of the neuron must give rise to a net dipole current to contribute to the EEG signal.
The geometry of the neuron must give rise to a net dipole current to contribute to the EEG signal.
- A large number of neurons have to be active simultaneously to generate a measurable EEG signal.
- Pyramidal neurons are spatially aligned and perpendicular to the cortical surface.
Pyramidal neurons are spatially aligned and perpendicular to the cortical surface.
- Thus, EEG represents mainly the postsynaptic potentials of pyramidal neurons close to the recording electrode.
- The electrical activity from deeper generators gets dispersed and attenuated by volume conduction effects.



Primary intracellular currents give rise to volume currents



MEG measures the changes in the magnetic field generated by an electric current (Sarvas 1987, Hämäläinen 1993)

These magnetic fields are mainly induced by primary currents based on excitatory activity (Okada et al. 1997)

Volume currents yield potential differences on the scalp that can be measured by EEG.



- The connection between electricity and magnetism was first discovered by Hans Christian Orsted in 1819.
- He demonstrated that a magnetic compass needle was affected by a current passing through a circuit.
- An electrical dipole is always surrounded by a corresponding magnetic field.
- The polarity of the field is determined by the direction of the current.

History



1929: **Hans Berger** developed the electroencephalography (=graphic representation of the difference in voltage between two different cerebral locations plotted over time) following the studies of Richard Caton in non-human animal species.

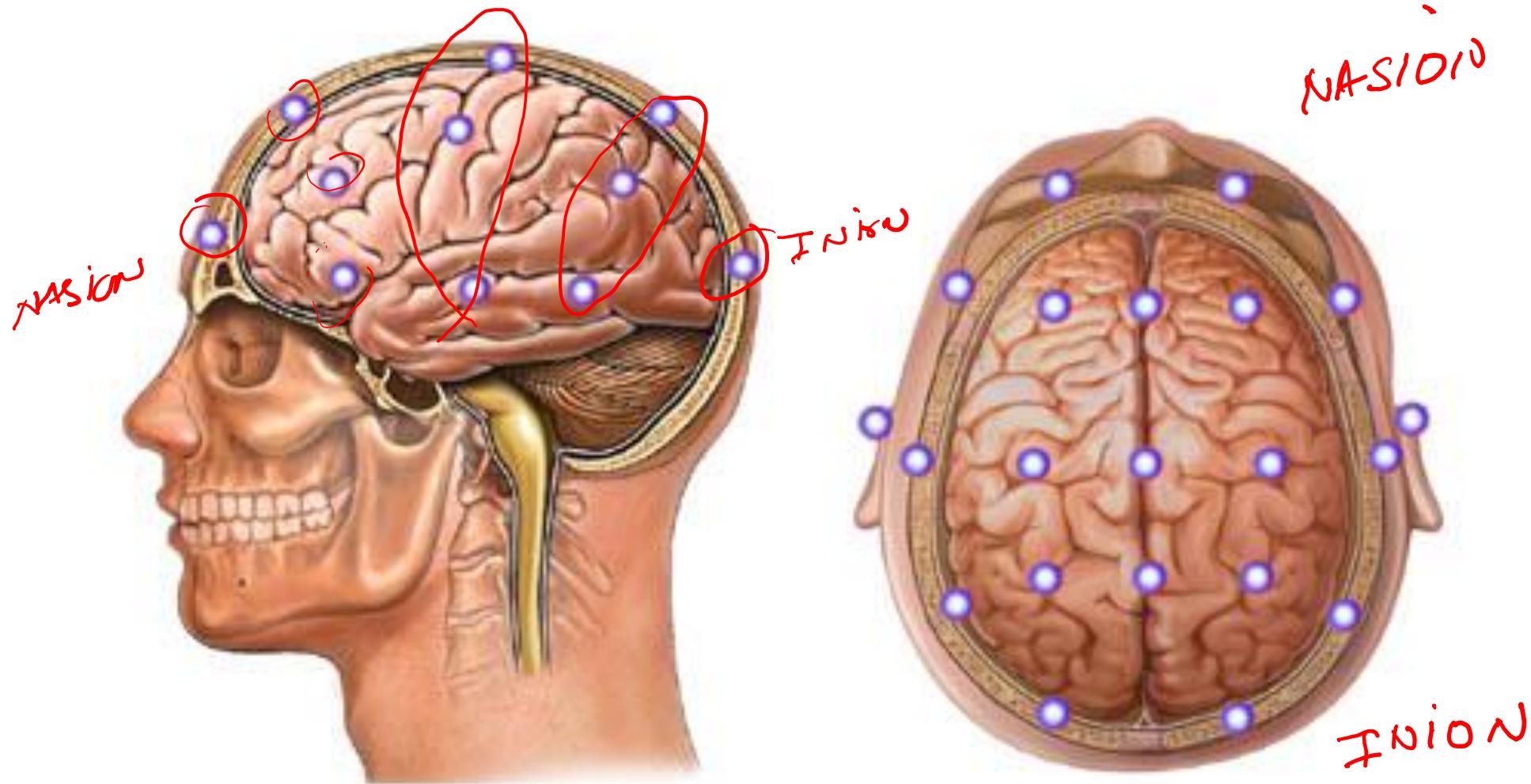
He described the human alpha and beta rhythms.

8-13 Hz
Berger waves

High density EEG recording



Electrode placing locations in EEG



Electrode location in EEG

The names of the electrode sites use **alphabetical abbreviations** that identify the lobe or area of the brain to which each electrode refers:

F = frontal

Fp = frontopolar

T = temporal

C = central

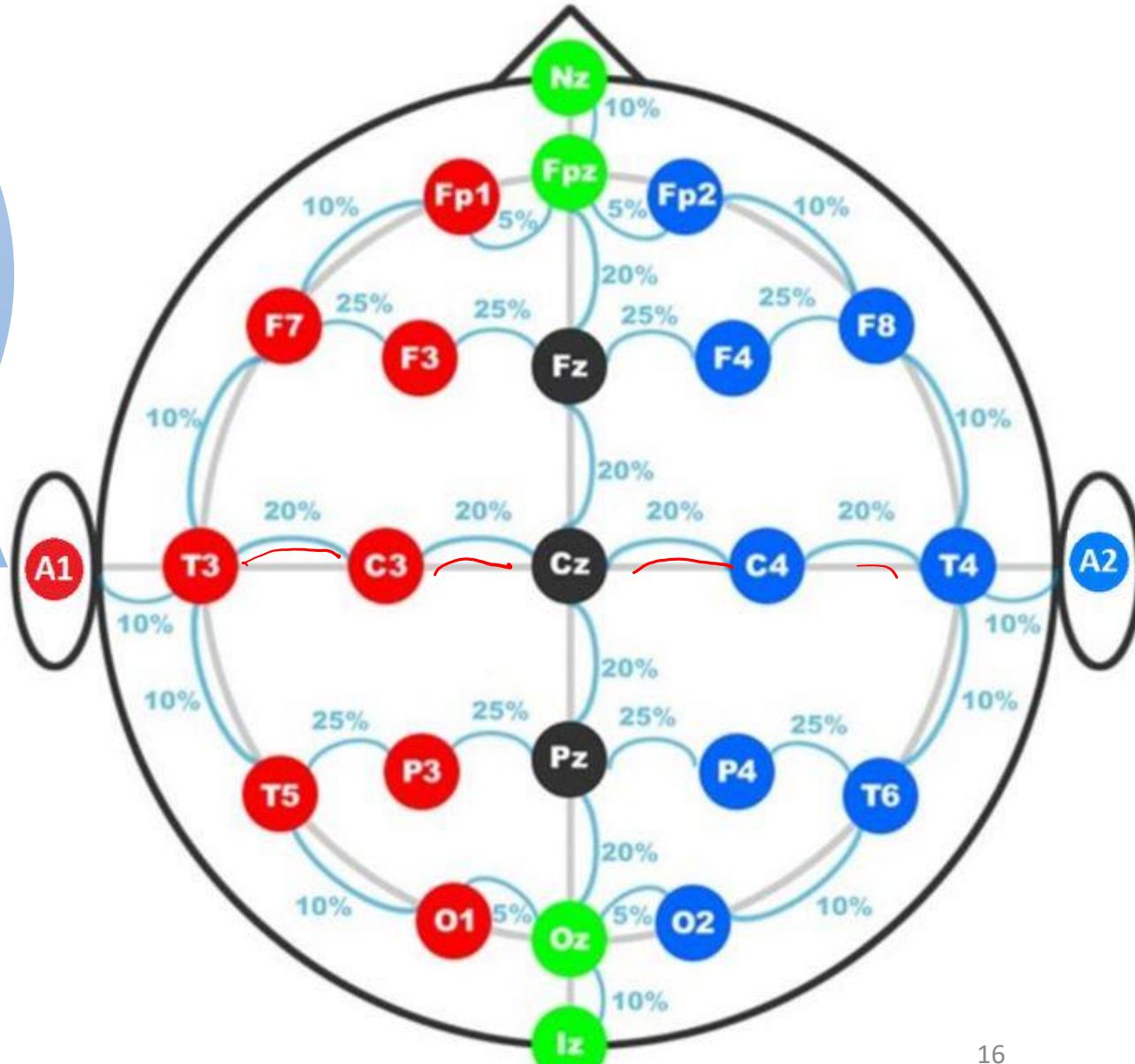
P = parietal

O = occipital

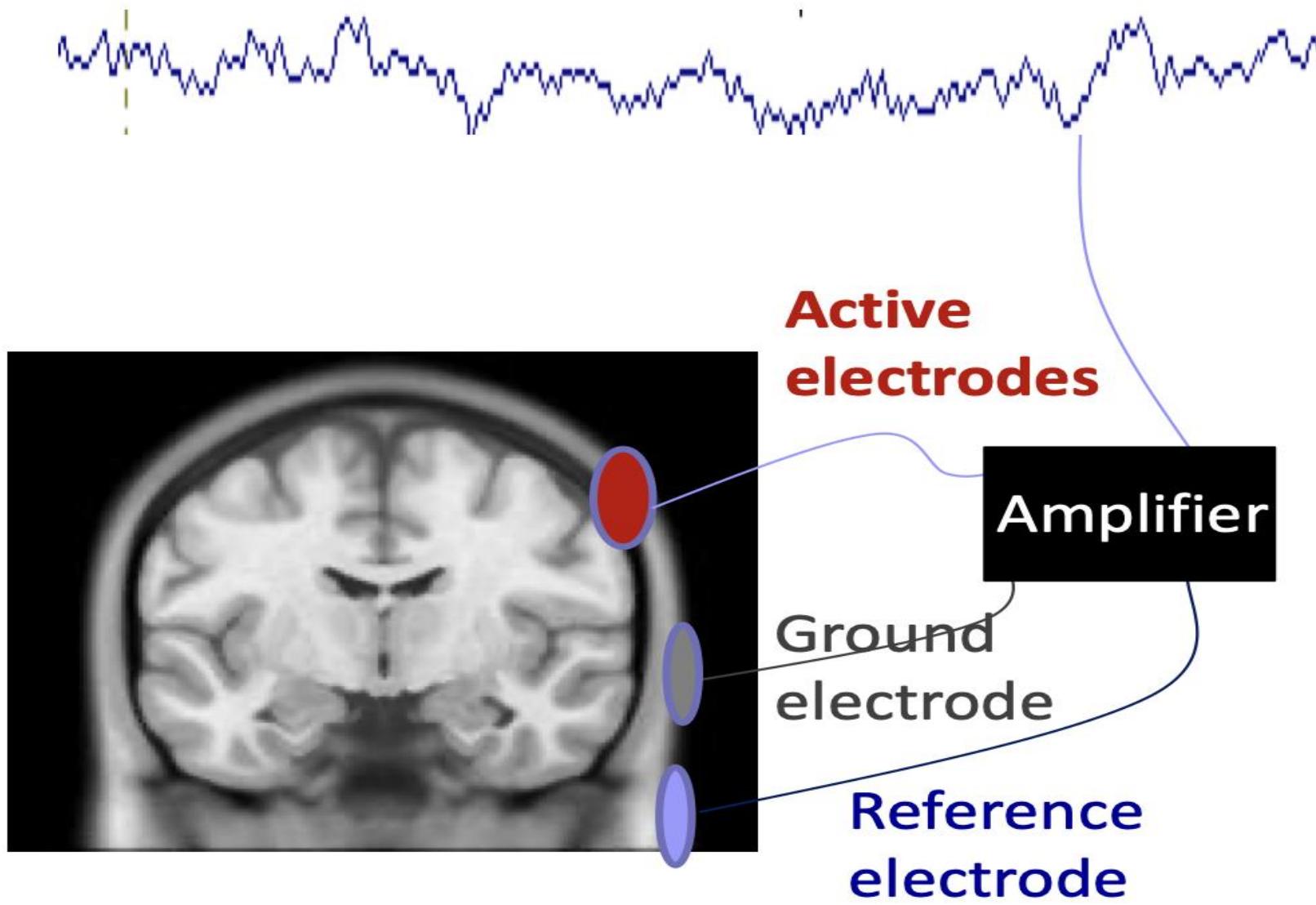
A = auricular (ear electrode)

“**z**” refers to an electrode placed on the mid-line

- ❖ **Even numbers** denote the **right side** of the head and **odd numbers** the left side of the head.



Measuring EEG...



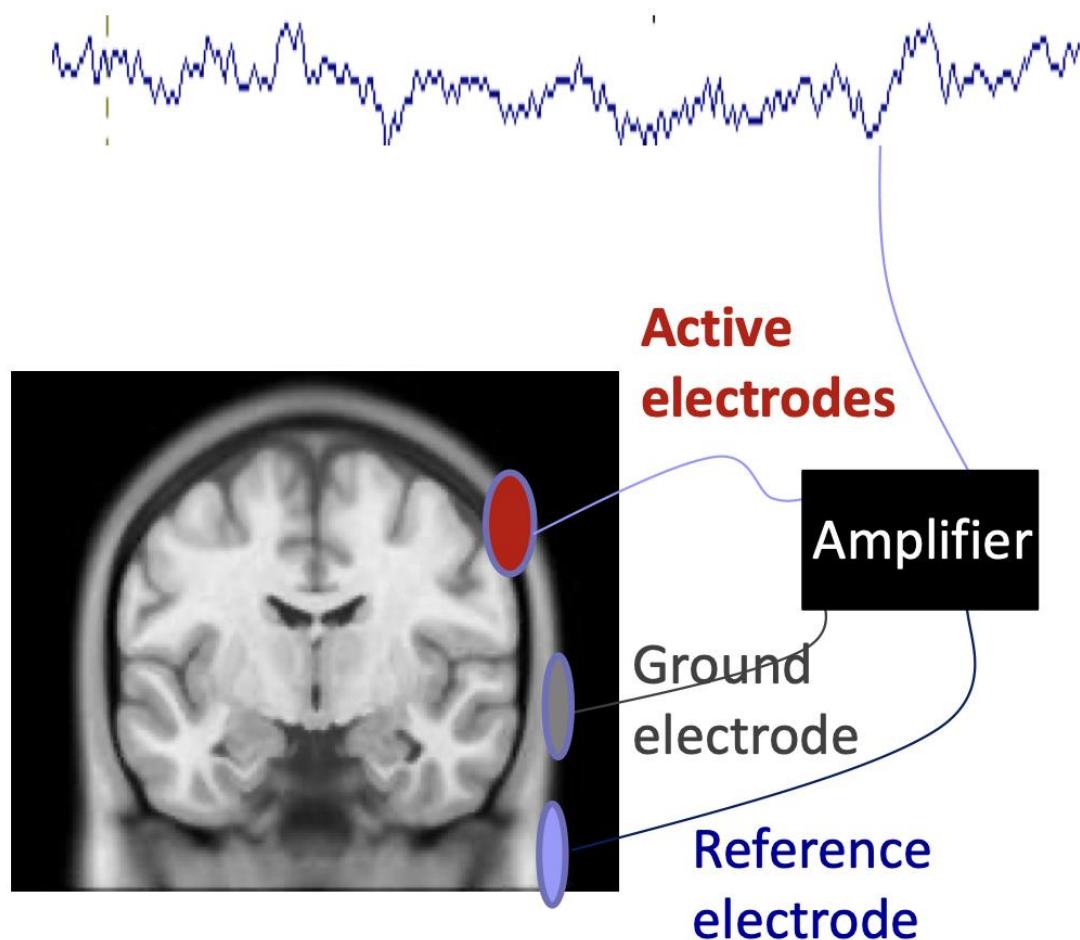
Measuring EEG...

Electric fields affecting measurements:

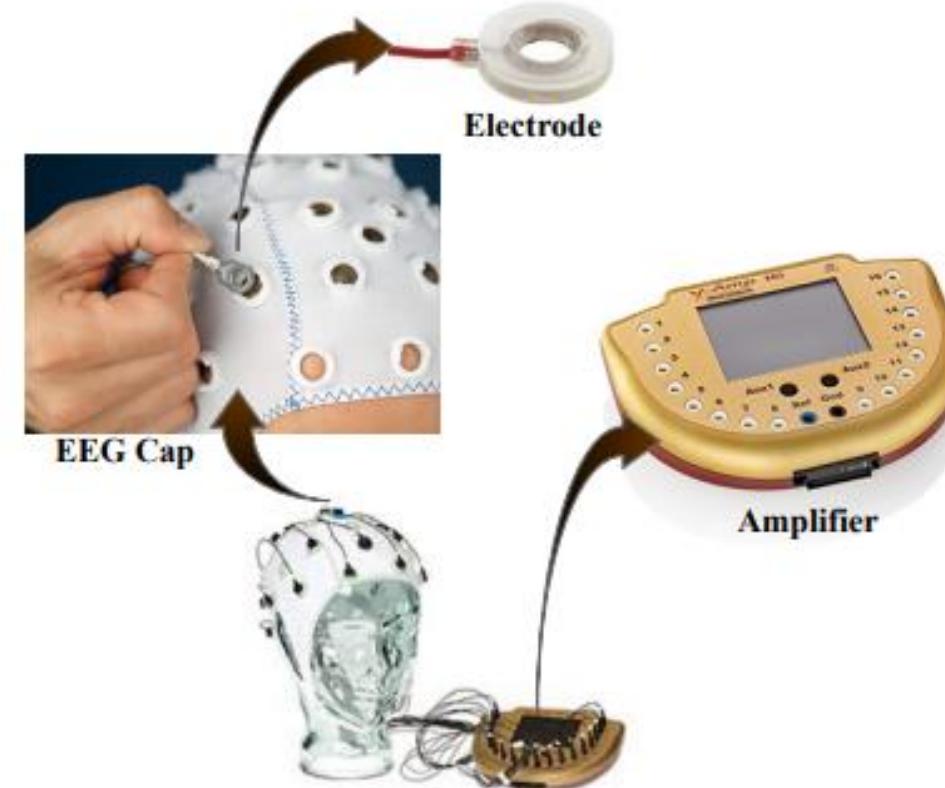
1. Static electric current
2. Electric noise
3. Brain activity

Ground = difference between the participant and the amplifier

- Subtracted from the active and reference electrode activity: A-G, R-G
- is the reference point in an **electrical circuit** from which voltages are measured, a common return path for **electric current**, or a direct physical connection to the **Earth**.



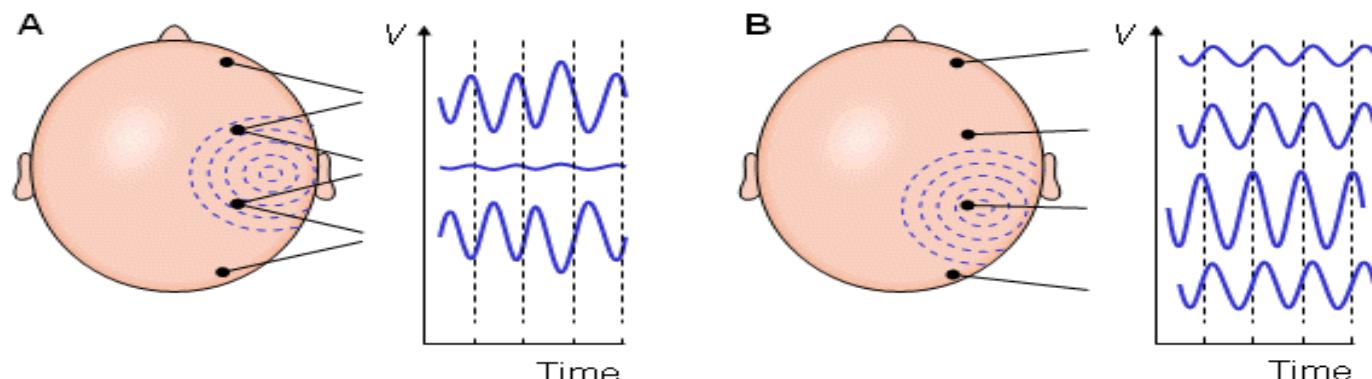
An EEG Device



Other Accessories

Measuring EEG...

- EEG records potential differences at the scalp using a set of electrodes and a reference.
- The ground electrode is important to eliminate noise from the amplifier circuit.
- The representation of the EEG channels is referred to as a montage
 - Unipolar/Referential \Rightarrow potential difference between electrode and designated reference
 - Bipolar \Rightarrow represents difference between adjacent electrodes (e.g. ECG, EOG)
- Potential differences are then amplified and filtered



Thank you!!



EEG Paradigms

Course Instructor

Dr. Annushree Bablani

Acknowledgments: Dr Sreeja SR

Direct (noninvasive) interfaces in EEG

- An event-related potential (ERP) is any measured brain response that is directly the result of a thought or perception. More formally, it is any stereotyped electrophysiological response to an internal or external stimulus.
- Direct Interfaces via EEG
 - VEP – Visual Evoked Potential
 - AEP – Auditory Evoked Potential
 - SSVEP – Steady-State Visual Evoked Potential
 - P300 – ERP elicited by infrequent, task-relevant stimuli.
 - ERS/ERD – Event related synchronization/desynchronization
 - SCP – Slow cortical potentials

Categorization of EEG based BCI paradigms

Evoked (Endogenous / Asynchronous)

- Subject must pay attention for a certain time to external cues (e.g. flashes, sounds, etc.)
- Cue-based

Spontaneous (Exogenous / Synchronous)

- No continuous attention to specific stimulus is necessary
- User-driven



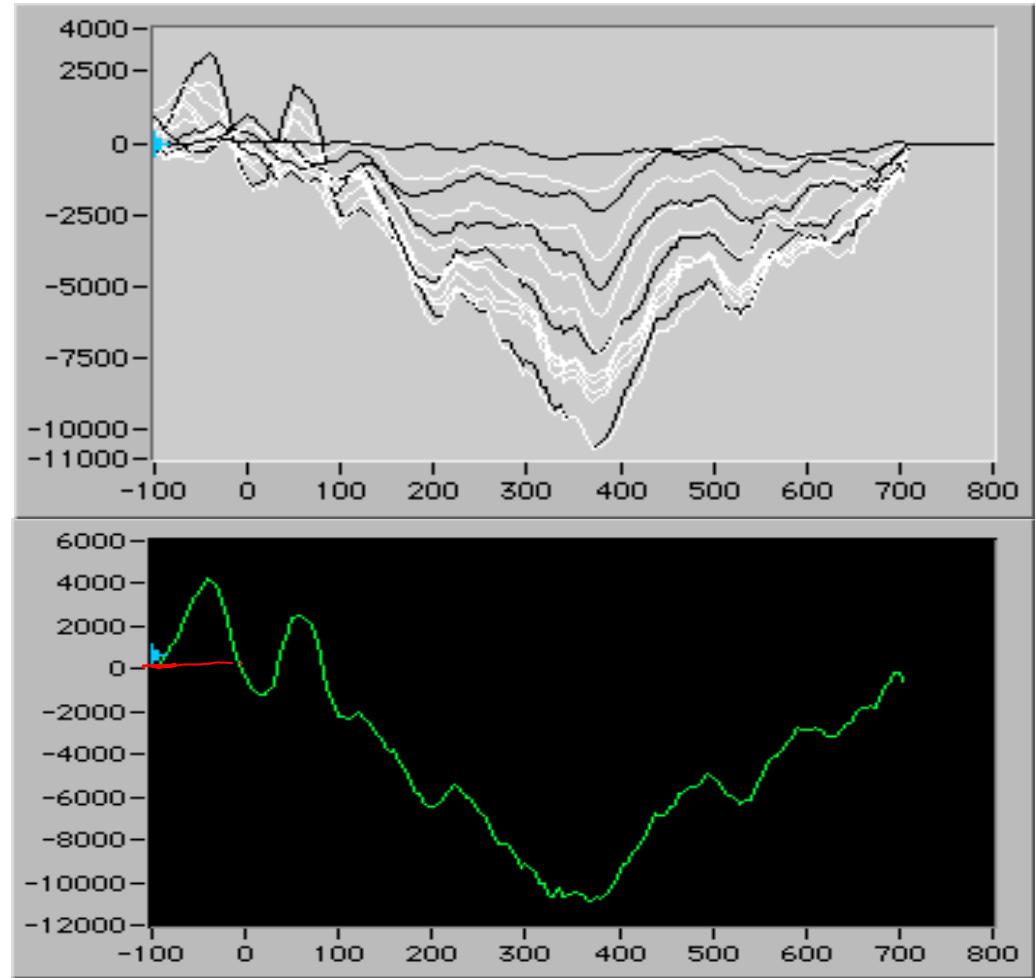
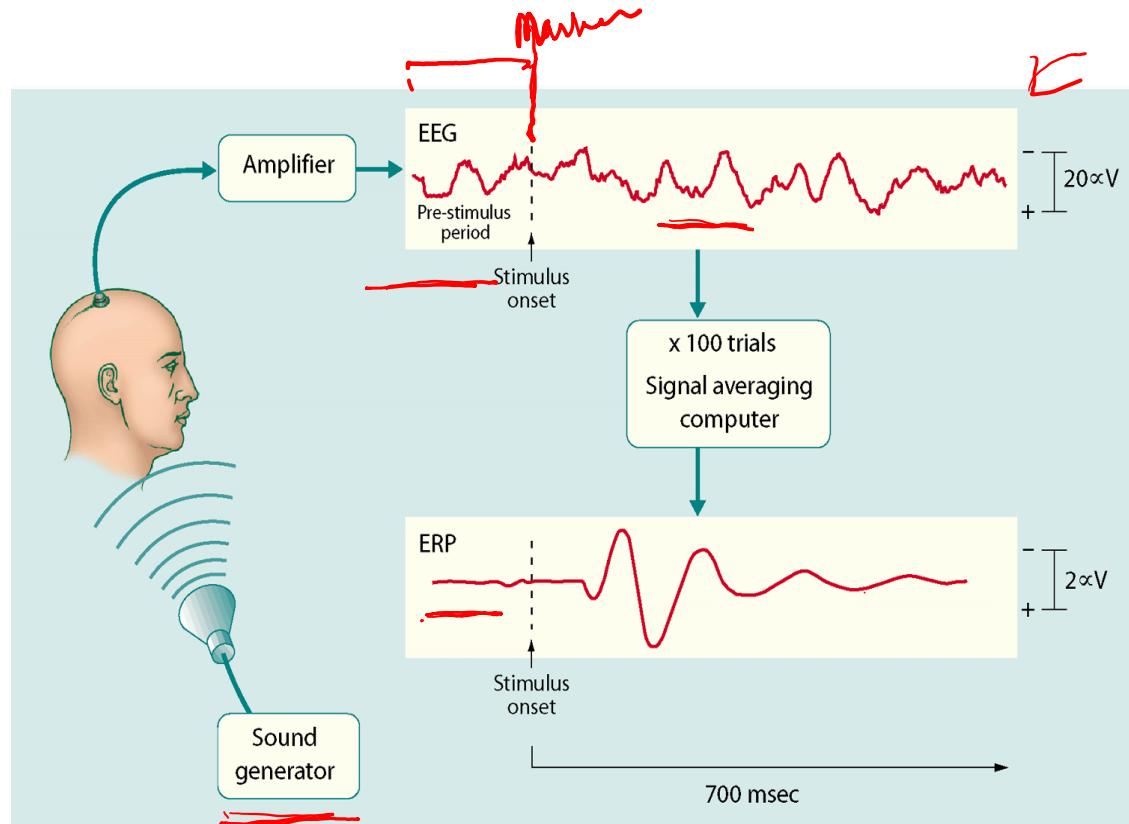
Categorization of EEG based BCI paradigms

ERD		Spontaneous
P300	→	Evoked
SSEP/AEP/VEP	→	Evoked
SCP	→	Spontaneous

Event Related Potentials (ERP)

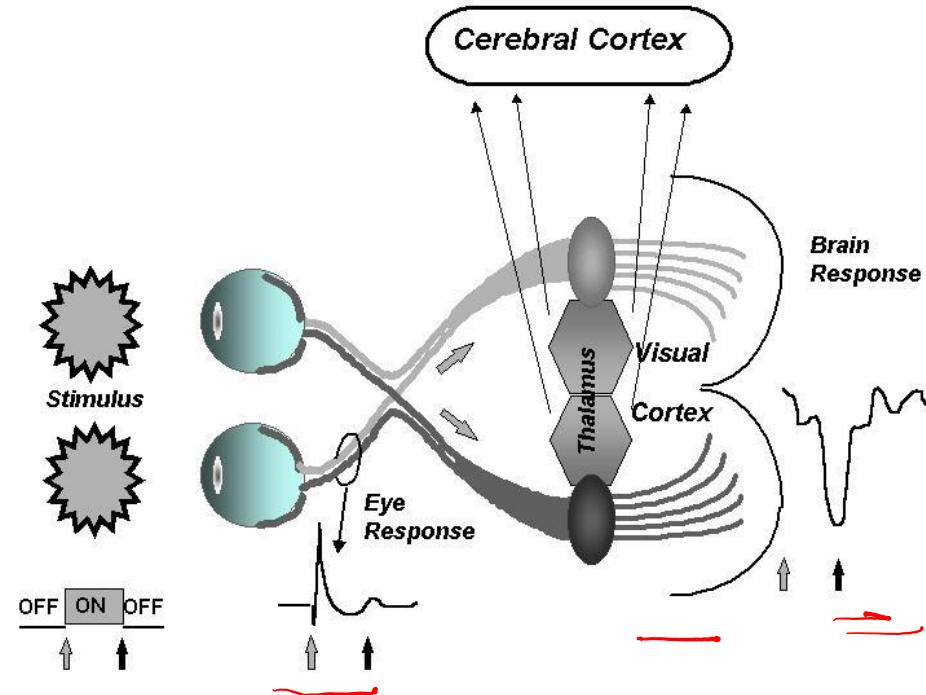
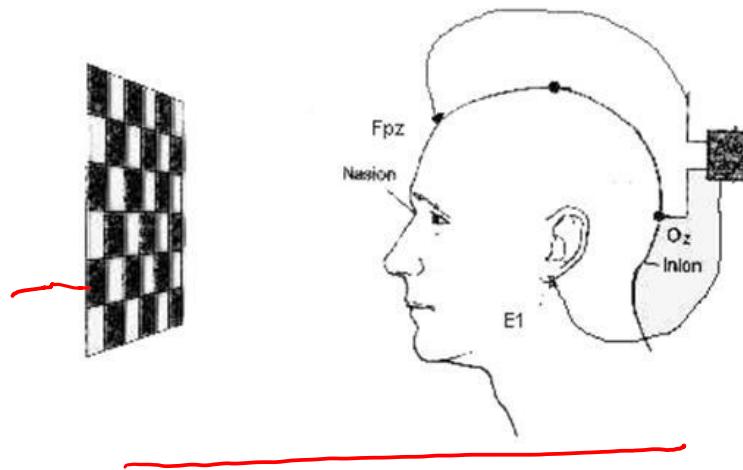
→ *reflections* → +ve P100
↓ -ve N100

- Averaging of trials following a stimulus



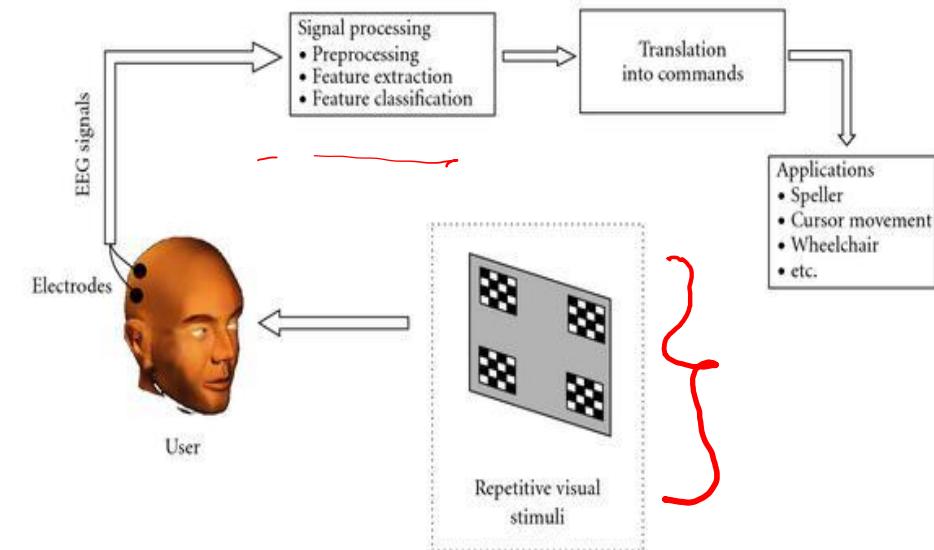
Visual Evoked Potential (VEP)

- Caused by Visual Stimulus
- Occurs with flashing lights (3-5 Hz)
- Have been used to monitor function during surgery for lesions involving the pituitary gland, optic nerve.
- Application:



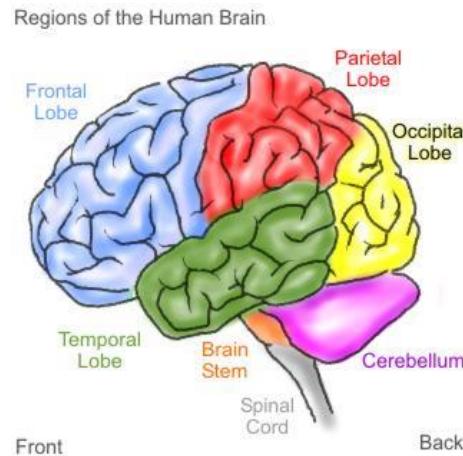
Steady-State Visual Evoked Potential (SSVEP)

- SSVEP are signals that are natural responses to visual stimulation at specific frequencies. When the retina is excited by a visual stimulus ranging from 3.5 Hz to 75 Hz, the brain generates electrical activity at the same (or multiples of) frequency of the visual stimulus.
- Excellent signal-to-noise ratio and relative immunity to artifacts.
- Applications:
 - SSVEP-controlled robots (Boston University)
 - User-friendly interface



P300 ← ER^I

- P300 is thought to reflect processes involved in stimulus evaluation or categorization.
- It is usually elicited using the oddball paradigm in which low-probability target items are inter-mixed with high-probability non-target (or "standard") items.
- Results in a positive curve on EEG after 300ms.
- Strongest signal at parietal lobe.

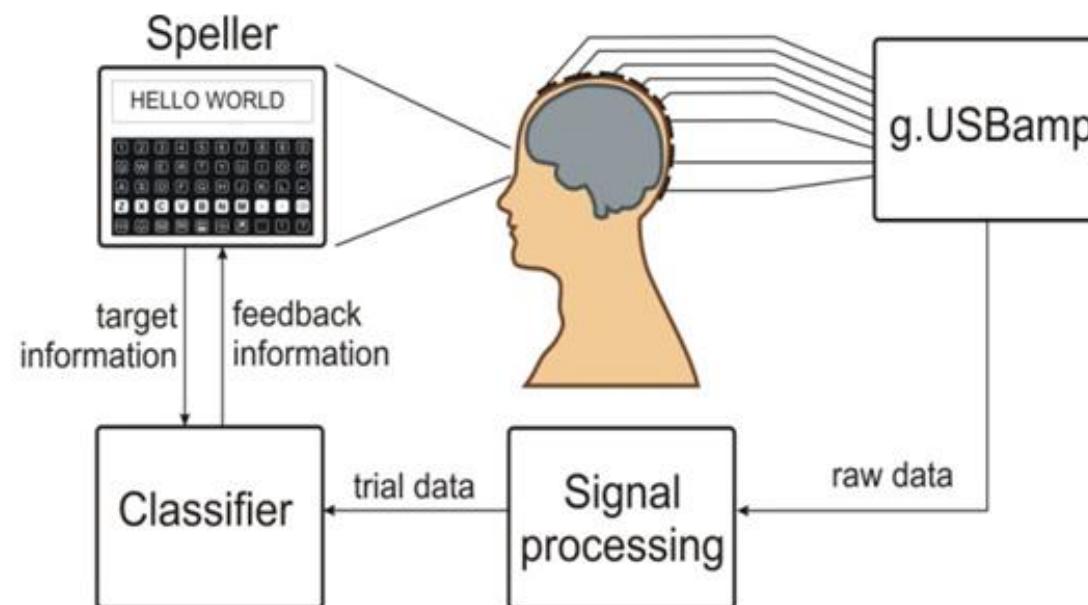


- 6x6 matrix of symbols
- Subject concentrates on a symbol (i.e. cell)
- Each row and column flashes twice
 - i.e., 2 target flashes vs. 10 non-target flashes
 - random order
 - for very short time (e.g. 100 ms)



P300

- (Farwell and Donchin 1988)
- 95% accuracy at 1 character per 26s

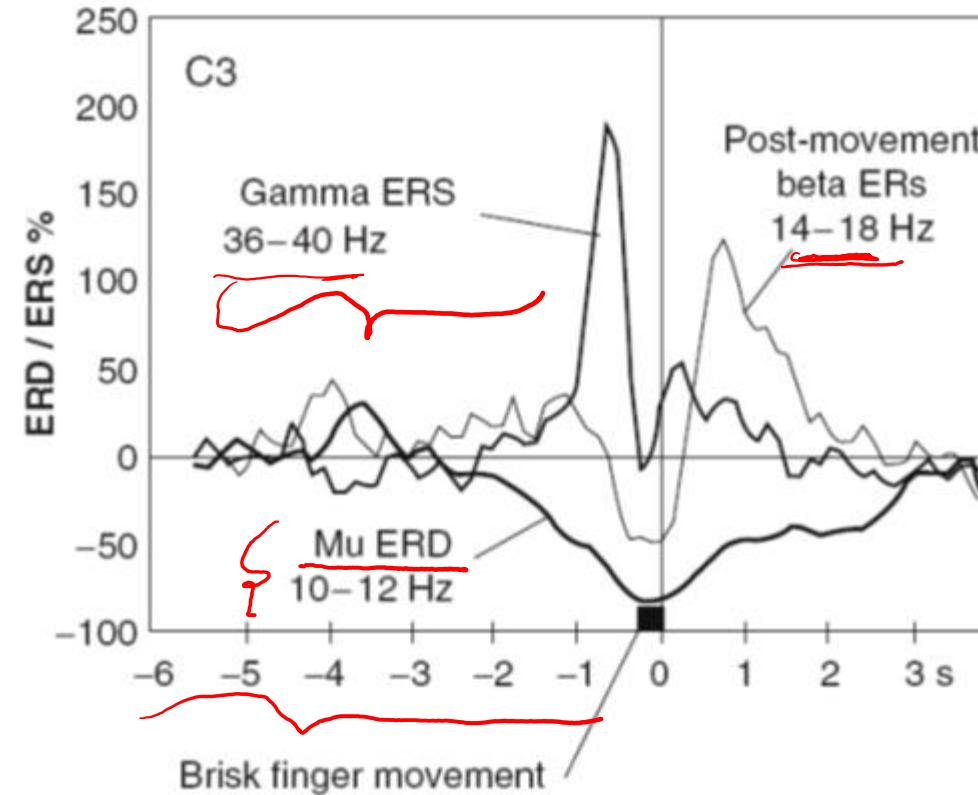


ERS/ERD

- Event-related desynchronization (ERD) and event-related synchronization (ERS) is the change of signal's power occurring in a given band relative to a reference interval.
- People have naturally occurred brain rhythms over areas of the brain concerned with touch and movement. When people imagine moving, these brain rhythms first become weaker, then stronger. These two changes are called ERD and ERS, respectively.
- **ERS**
 - oscillatory power increase
 - associated with activity decrease
- **ERD**
 - oscillatory power decrease
 - associated with activity increase

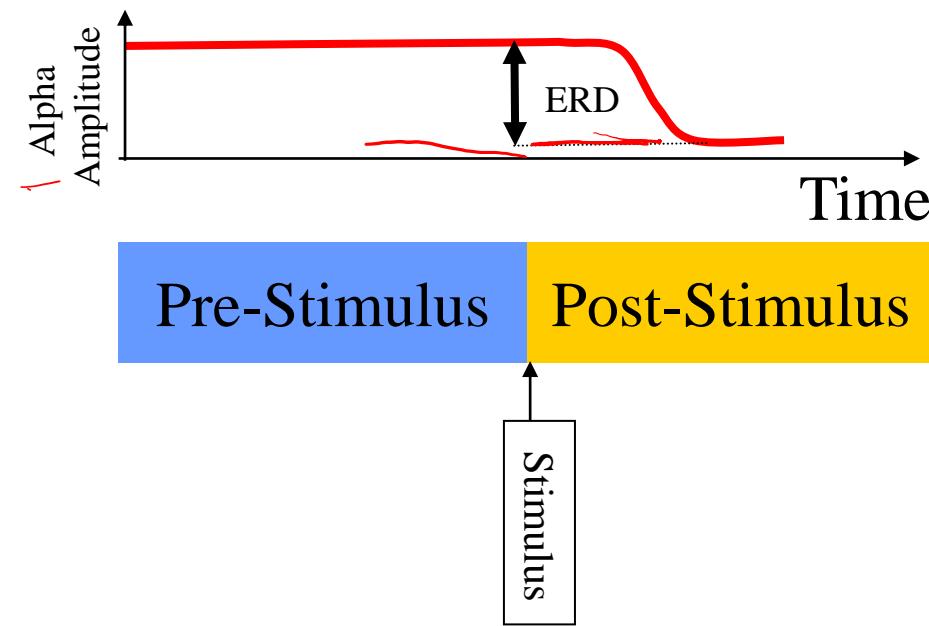
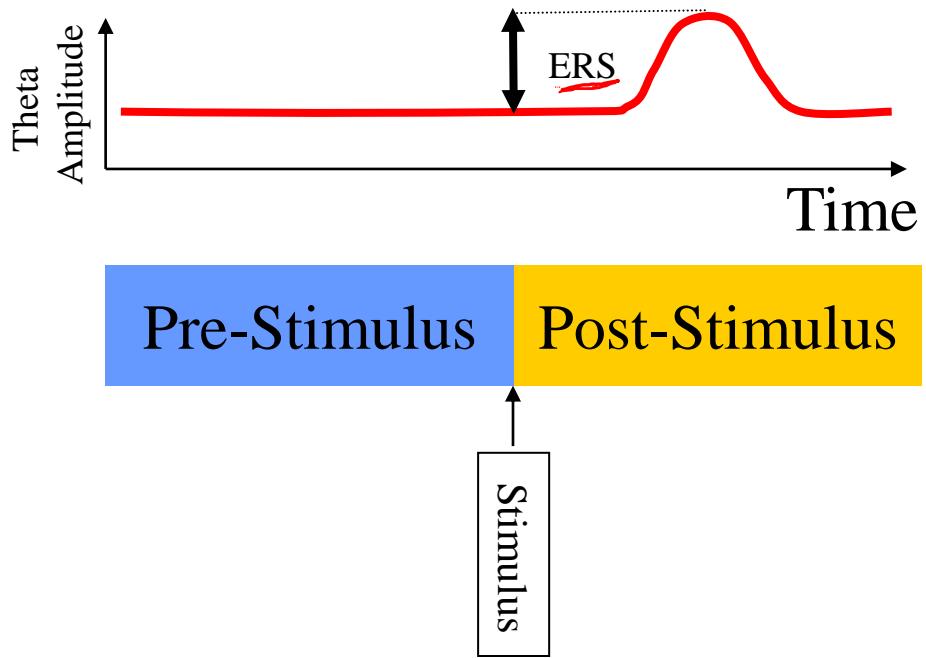
ERS/ERD

- The imagination of either a left or right hand movement results in:
 - An amplitude attenuation (Event-Related Desynchronization (ERD)) of μ (8-12Hz) and central beta EEG-rhythms (13-30Hz) at the contralateral sensorial motor representation area and,
 - in some cases, in an amplitude increase (Event-Related Synchronization (ERS)) within the γ -band (30-40Hz) at the ipsilateral hemisphere(6).

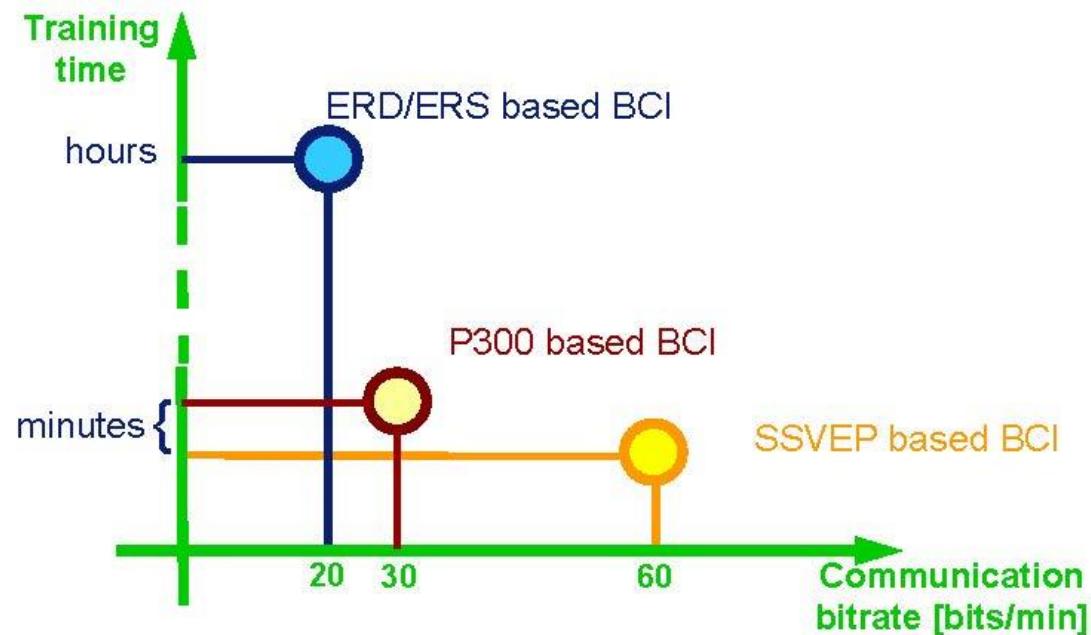


EEG recorded from C3 electrode.

4 8 13 * 2
8 13 * 2



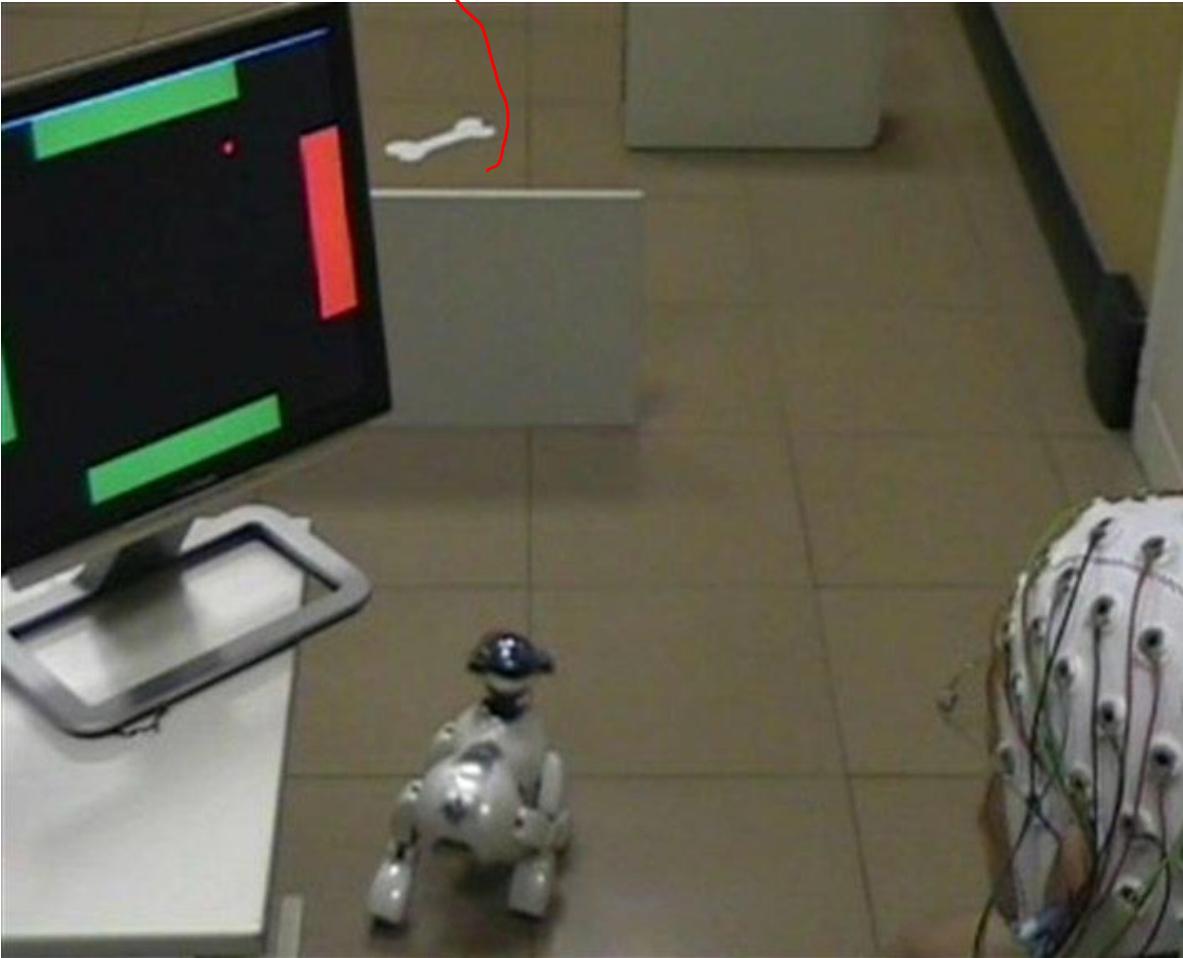
Communication Issues



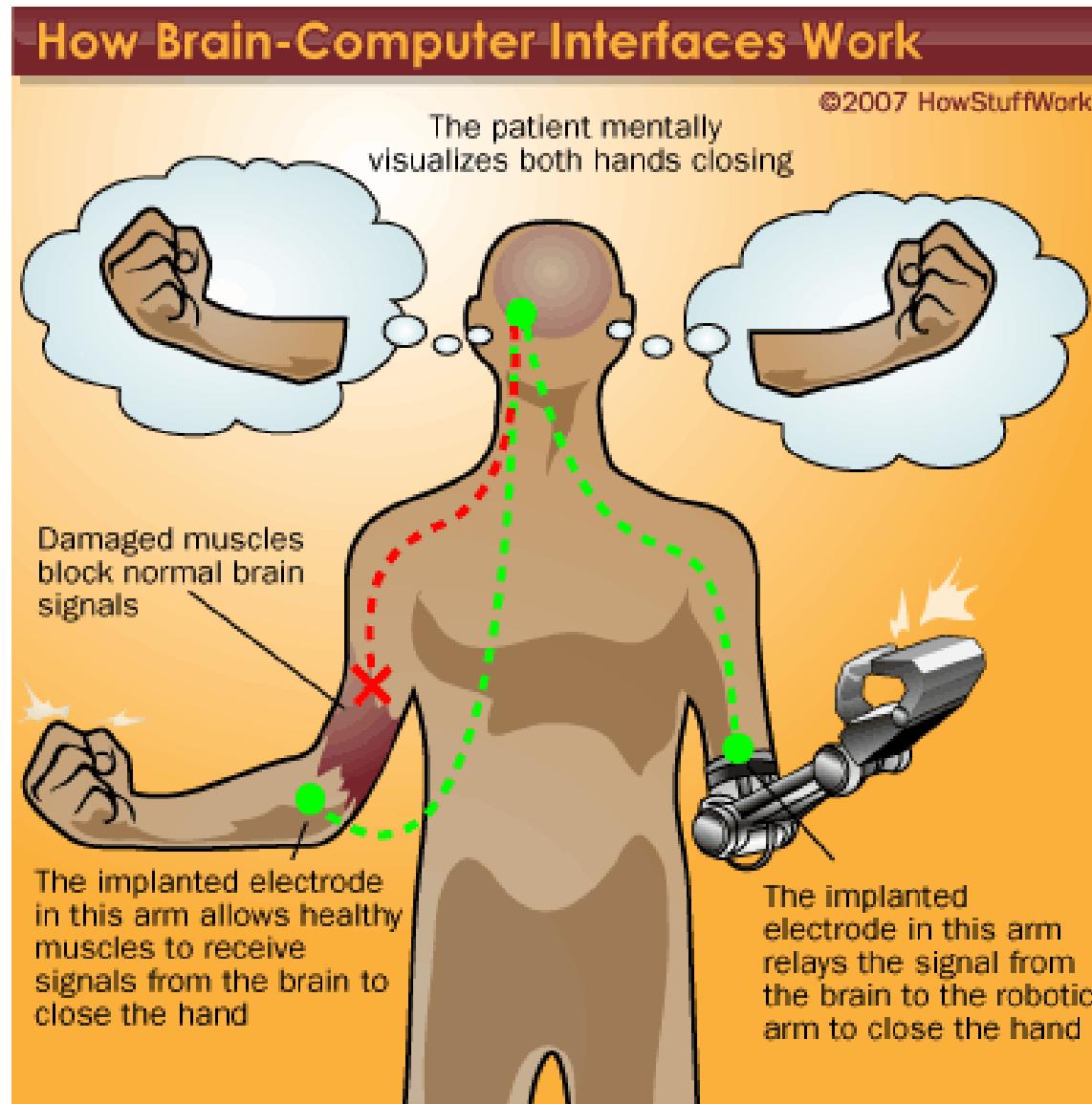
Typical training time versus communication bitrate for the three main types of noninvasive EEG based BCIs.

BCI Applications

BCI – operated robot



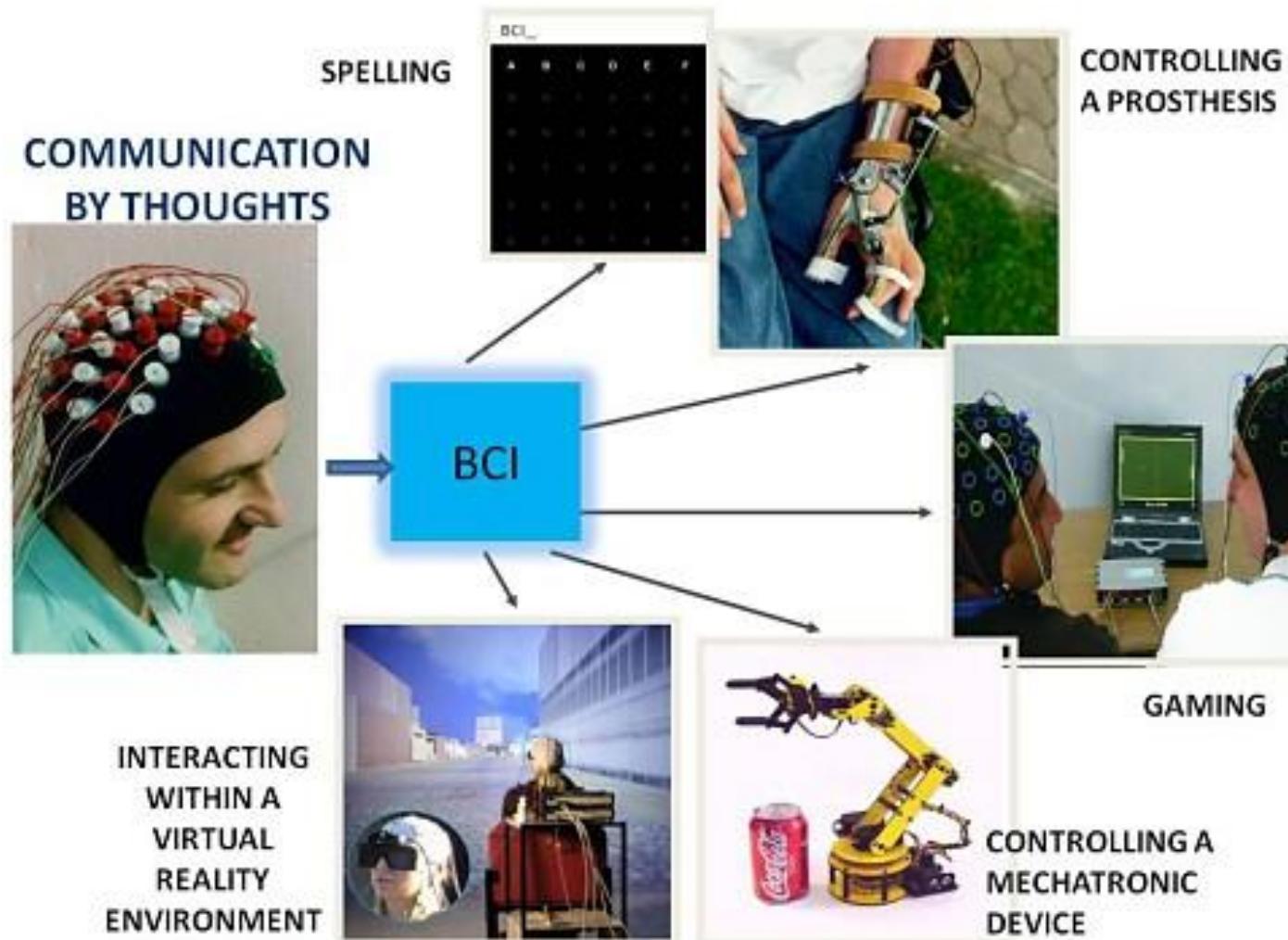
BCI Applications



BCI Applications



BCI Applications



Thank you!



EEG Variables

Course Instructor

Dr. Annushree Bablani

Acknowledgments: Dr. Sreeja S R

EEG

- Electroencephalogram (EEG) signals are useful for diagnosing various mental conditions such as epilepsy, memory impairments and sleep disorders.
- EEGs can indicate the general conscious state of a person, e.g., asleep, awake, anaesthetized, since each state is correlated with particular EEG patterns.
- A flat EEG (no electrical activity) is clinical evidence of death.

Why EEG?

- Hardware costs are significantly lower than those of most other techniques.
- EEG sensors can be used in more places than fMRI, SPECT, PET, MRS, or MEG, as these techniques require bulky and immobile equipment.
- EEG has very high temporal resolution, on the order of milliseconds rather than seconds, commonly recorded at sampling rates between 250 and 2000 Hz thus a valuable tool for research and diagnosis.
- EEG is relatively tolerant of subject movement, unlike most other neuro imaging techniques. There even exist methods for minimizing, and even eliminating movement artifacts in EEG data.
- EEG is silent, which allows for better study of the responses to auditory stimuli.
- EEG does not involve exposure to high-intensity (>1 Tesla) magnetic fields, as in some of the other techniques, especially MRI and MRS. These can cause a variety of undesirable issues with the data, and also prohibit use of these techniques with participants that have metal implants in their body, such as metal-containing pacemaker.
- EEG can be used in subjects who are incapable of making a motor response.
- EEG is a powerful tool for tracking brain changes during different phases of life. EEG sleep analysis can indicate significant aspects of the timing of brain development, including evaluating adolescent brain maturation.

EEG Disadvantages

- Low spatial resolution on the scalp. fMRI, for example, can directly display areas of the brain that are active, while EEG requires intense interpretation just to hypothesize what areas are activated by a particular response.
- EEG poorly determines neural activity that occurs below the upper layers of the brain (the cortex).
- Unlike PET and MRS, cannot identify specific locations in the brain at which various neurotransmitters, drugs, etc. can be found.
- Often takes a long time to connect a subject to EEG, as it requires precise placement of dozens of electrodes around the head and the use of various gels, saline solutions, and/or pastes to keep them in place. Whereas a general rule it takes considerably less time to prepare a subject for MEG, fMRI, MRS, and PET.

EEG Pioneers

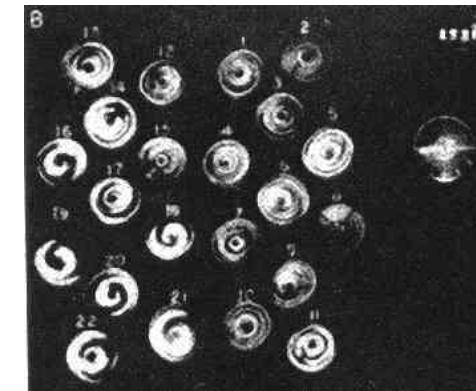
In 1929, Hans Berger

- Recorded brain activity from the closed skull
- Reported brain activity changes according to the functional state of the brain
 - Sleep
 - Hypnosis
 - Pathological states (epilepsy)



In 1957, Gray Walter

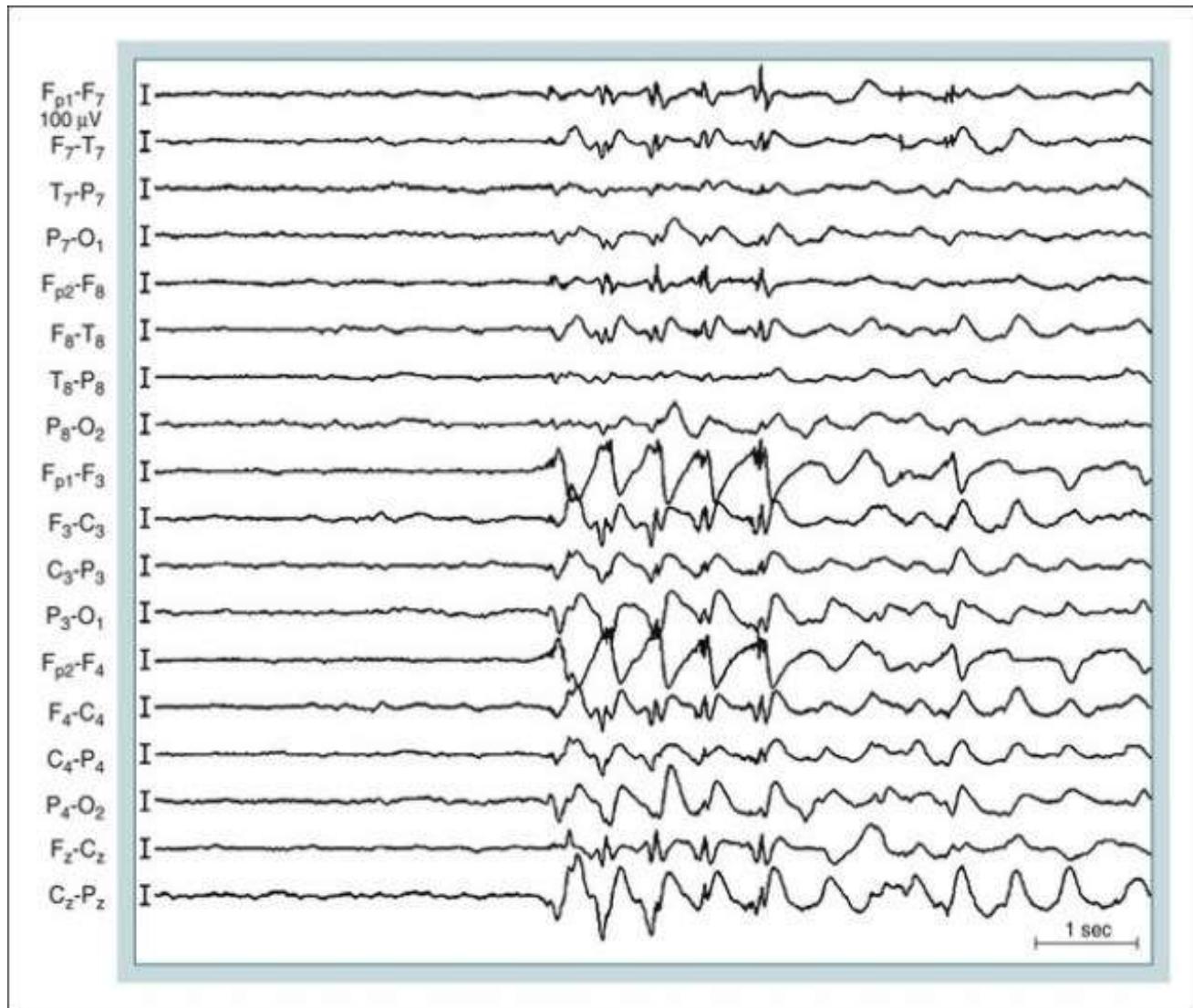
- Makes recordings with large numbers of electrodes
- Visualizes brain activity with the toposcope
- Shows that brain rhythms change according to the mental task demanded



Representation of EEG channels:

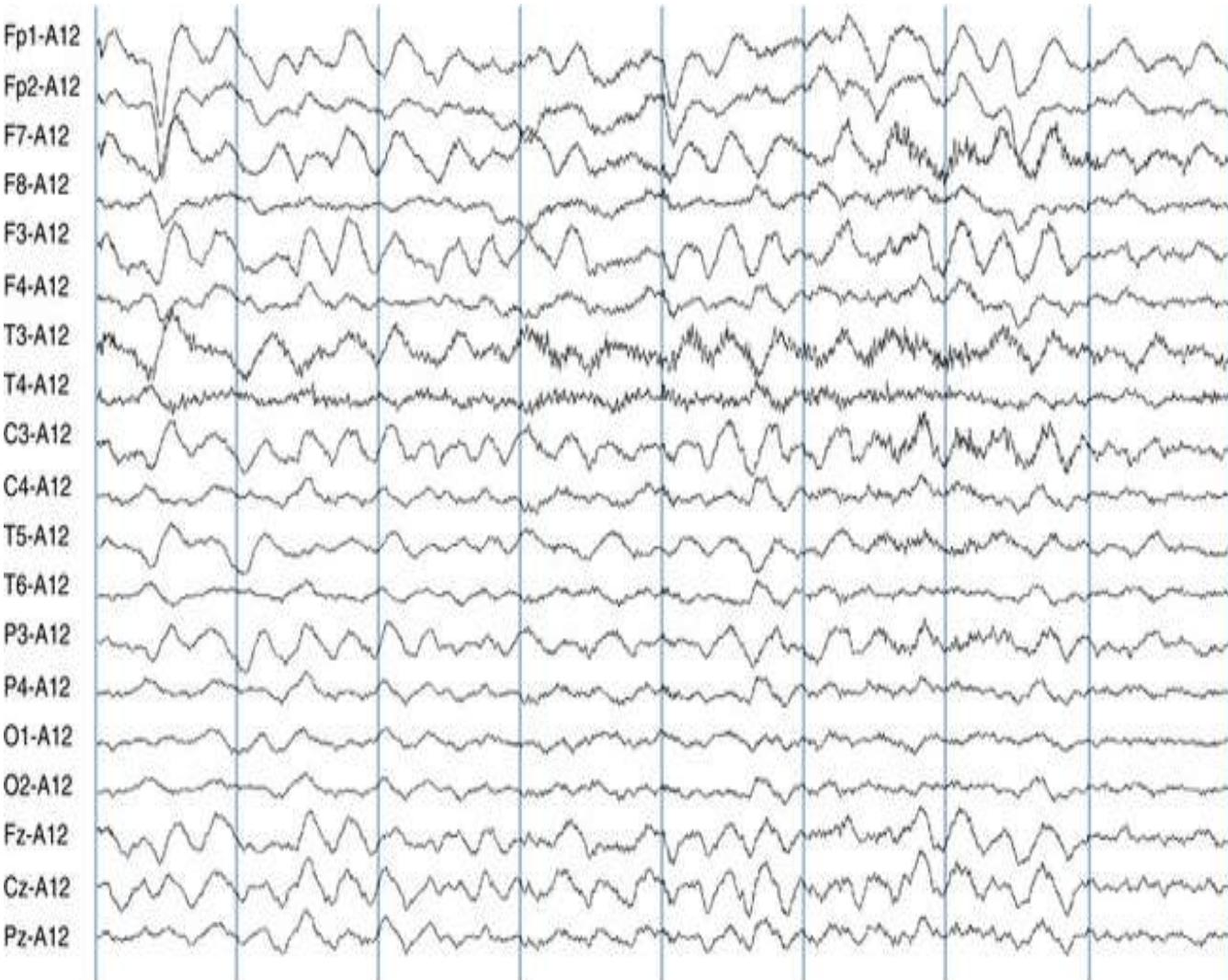
The representation of the EEG channels (i.e., waveform) is referred to as a **montage**.

- **Sequential montage:** Each channel represents the difference between two adjacent electrodes. The entire montage consists of a series of these channels. For example, the channel "Fp1-F3" represents the difference in voltage between the Fp1 electrode and the F3 electrode. The next channel in the montage, "F3-C3," represents the voltage difference between F3 and C3, and so on through the entire array of electrodes.



Representation of EEG channels:

- **Referential montage:** Each channel represents the difference between a certain electrode and a designated reference electrode. There is no standard position for this reference; it is, however, at a different position than the "recording" electrodes. Midline positions are often used because they do not amplify the signal in one hemisphere vs. the other. Another popular reference is "linked ears," which is a physical or mathematical average of electrodes attached to both earlobes or mastoids.

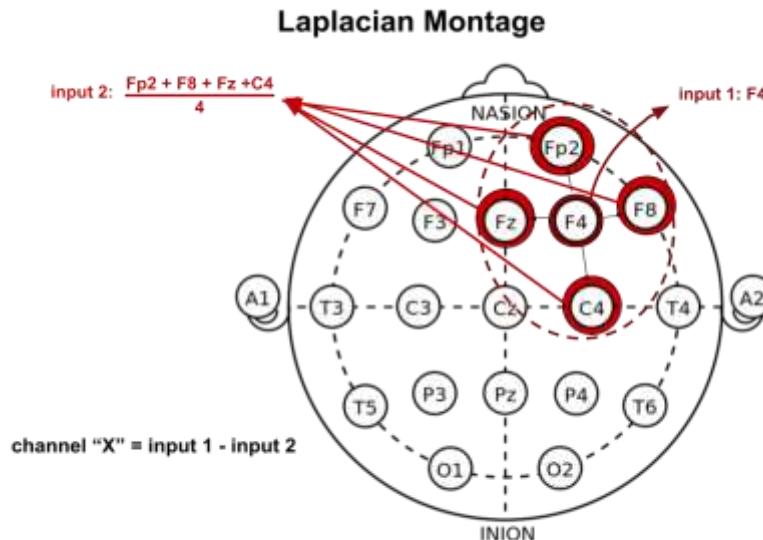
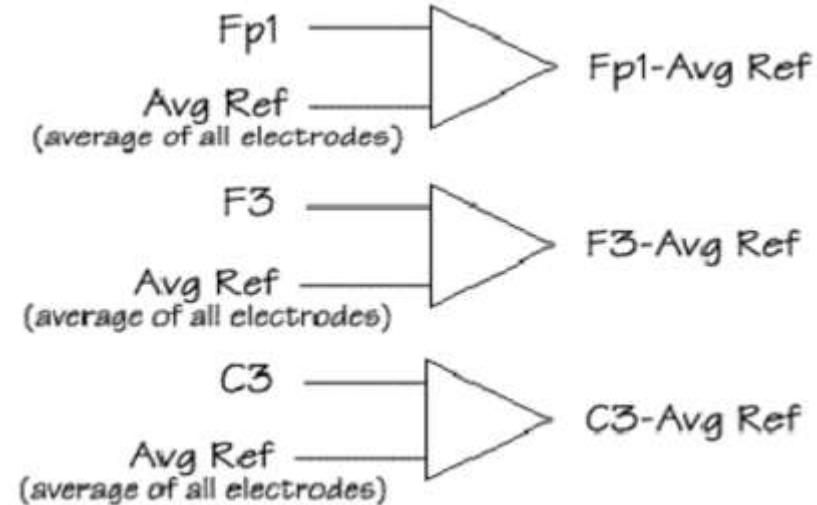


Representation of EEG channels:

- **Average reference montage:**

The outputs of all of the amplifiers are summed and averaged, and this averaged signal is used as the common reference for each channel.

- **Laplacian montage:** Each channel represents the difference between an electrode and a weighted average of the surrounding electrodes.



EEG Rhythms

- Generally grouped by frequency: (amplitudes are about 100 μ V max)

Type	Frequency	Location	Use
Delta	<4 Hz	everywhere	occur during sleep, coma
Theta	4-7 Hz	temporal and parietal	correlated with emotional stress (frustration & disappointment)
Alpha	8-15 Hz	occipital and parietal	reduce amplitude with sensory stimulation or mental imagery
Beta	16-30 Hz	parietal and frontal	can increase amplitude during intense mental activity
Gamma	>30 Hz	Somatosensory cortex	A decrease in gamma-band activity is associated with cognitive decline
Mu	8-12 Hz	frontal (motor cortex)	diminishes with movement or intention of movement
Lambda	sharp, jagged	occipital	correlated with visual attention
Vertex			higher incidence in patients with epilepsy or encephalopathy

Alpha Rhythm

Frequency: 8 – 15 Hz

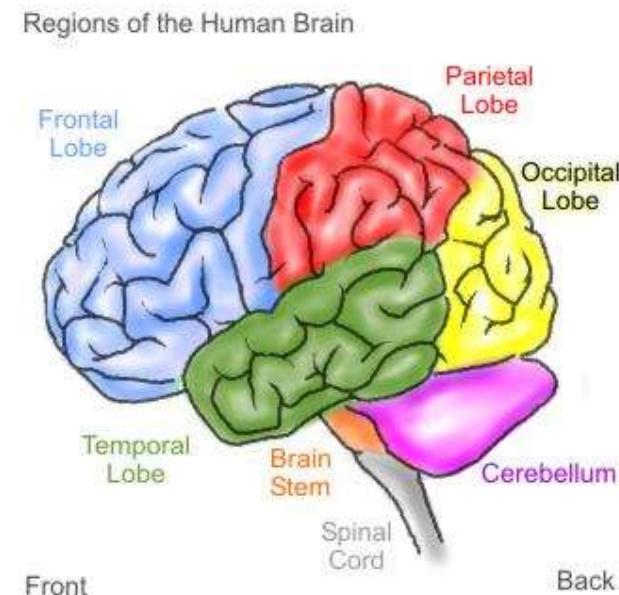
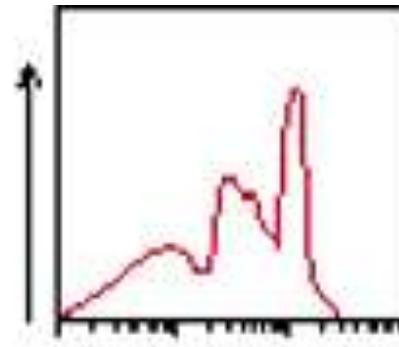
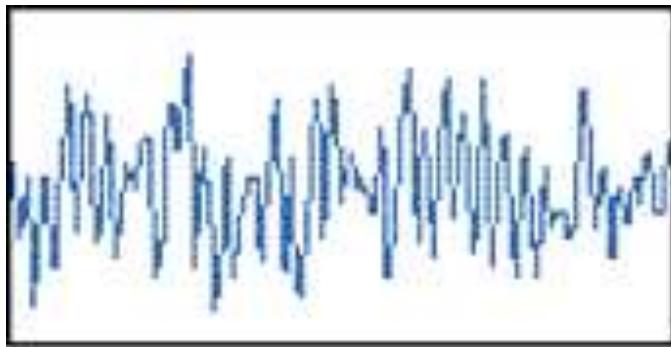
Amplitude: 5 – 100 microVolt

Location: Occipital, Parietal

State of Mind: Alert Restfulness

Source: Oscillating thalamic pacemaker neurons

Alpha blockade occurs when new stimulus is processed



Beta Rhythm

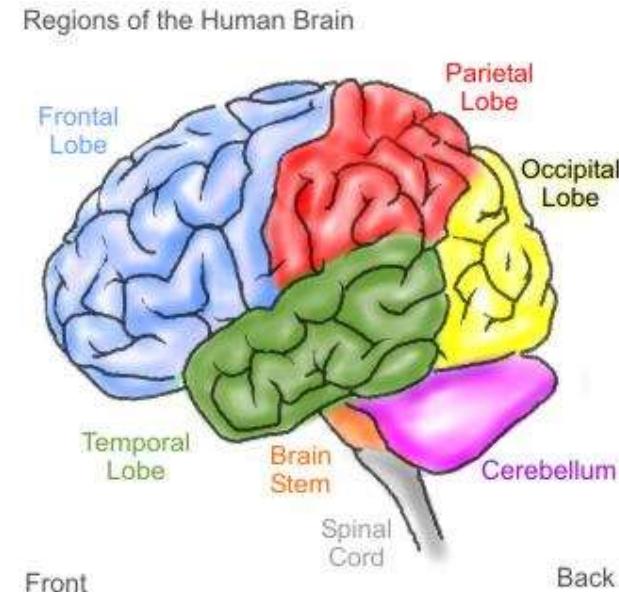
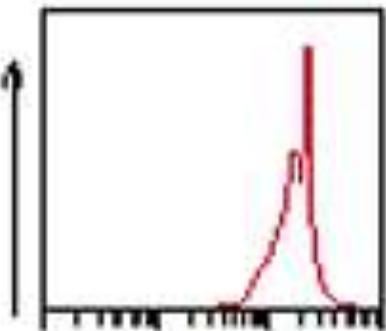
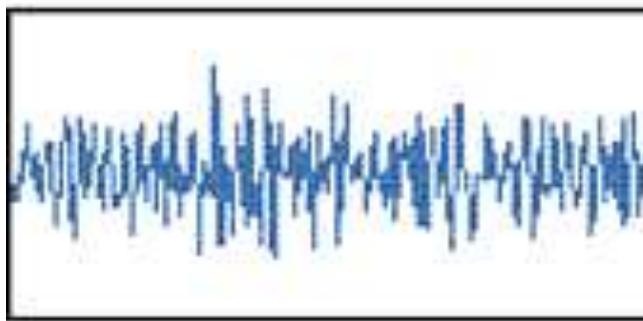
Frequency: 16 – 30 Hz

Amplitude: 2 – 20 microVolt

Location: Frontal

State of Mind: Mental Activity

Reflects specific information processing between cortex and thalamus



Delta Rhythm

Frequency: 1 – 4 Hz

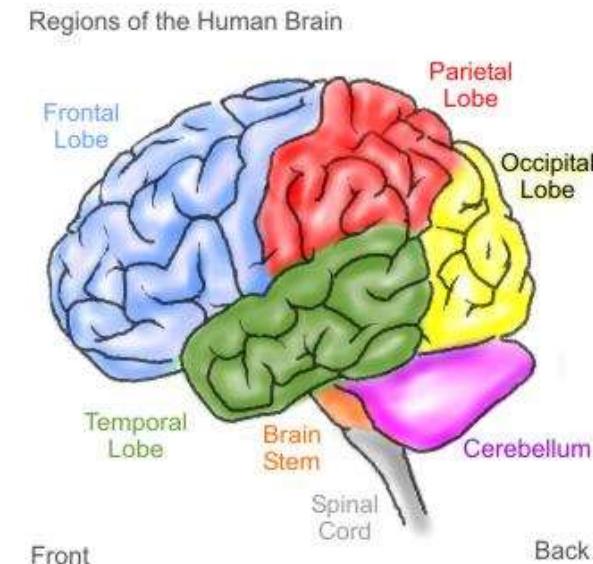
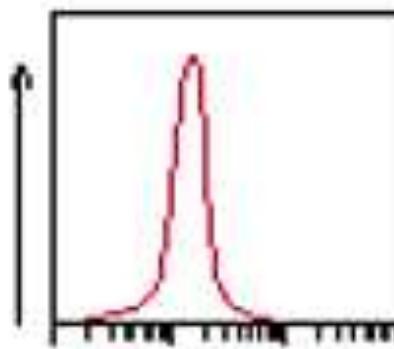
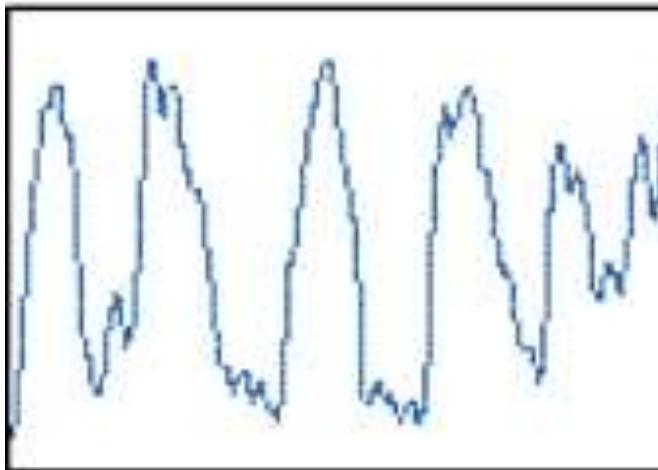
Amplitude: 20 – 200 microVolt

Location: Variable

State of Mind: Deep sleep

Oscillations in Thalamus and deep cortical layers

Usually inhibited by ARAS (Ascending Reticular Activation System)



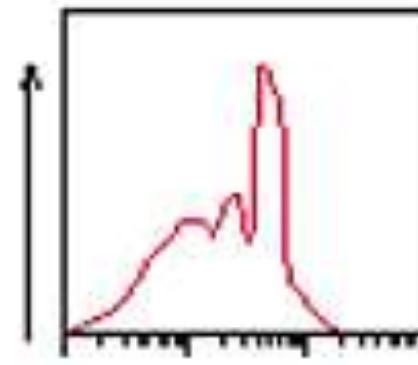
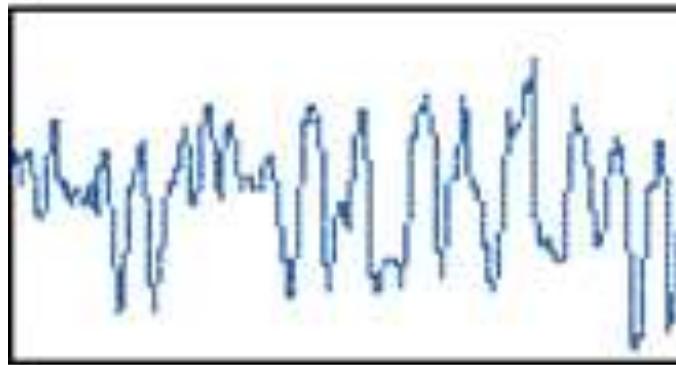
Theta Rhythm

Frequency: 4 – 7 Hz

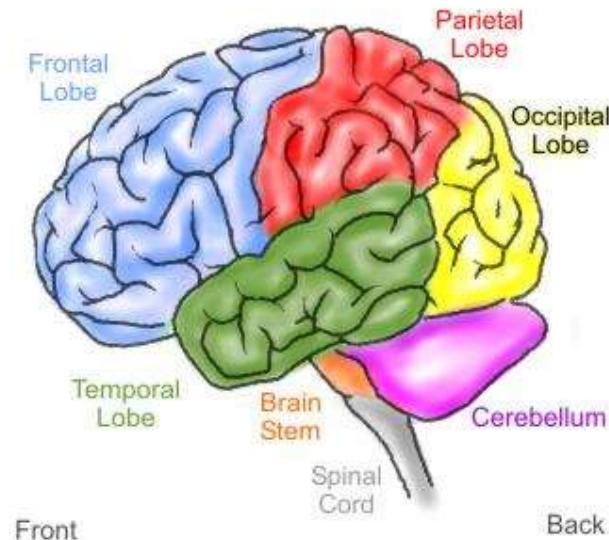
Amplitude: 5 – 100 microVolt

Location: Frontal, Temporal

State of Mind: Sleepiness



Regions of the Human Brain



Mu Waves

- Studied since 1930s
- Found in Motor Cortex
- Amplitude suppressed by Physical Movements, or *intent to move physically*
- (Wolpaw, et al 1991) trained subjects to control the mu rhythm by visualizing motor tasks to move a cursor up and down (1D)
- (Wolpaw and McFarland 2004) used a linear combination of Mu and Beta waves to control a 2D cursor.
- Weights were learned from the users in real time.
- Cursor moved every 50ms (20 Hz)
- 92% “hit rate” in average 1.9 sec

Alpha and Beta Waves

- Studied since 1920s
- Found in Parietal and Frontal Cortex
- Relaxed - Alpha has high amplitude
- Excited - Beta has high amplitude
- So, Relaxed -> Excited
means Alpha -> Beta

Variables used in EEG measurement:

Frequency:

- Frequency refers to rhythmic repetitive activity (in Hz). The frequency of EEG activity can have different properties including:
- **Rhythmic.** EEG activity consisting in waves of approximately constant frequency.
- **Arrhythmic.** EEG activity in which no stable rhythms are present.
- **Dysrhythmic.** Rhythms and/or patterns of EEG activity that characteristically appear in patient groups or rarely seen in healthy subjects.

Variables used in EEG measurement:

Voltage: Voltage refers to the average voltage or peak voltage of EEG activity.

- **Attenuation** (synonyms: suppression, depression). Reduction of amplitude of EEG activity resulting from decreased voltage.
- **Hypersynchrony.** Seen as an increase in voltage and regularity of rhythmic activity, or within the alpha, beta, or theta range. The term implies an increase in the number of neural elements contributing to the rhythm.
- **Paroxysmal.** Activity that reaching (usually) quite high voltage and ending with an abrupt return to lower voltage activity. Though the term does not directly imply abnormality, much abnormal activity is paroxysmal.

Variables used in EEG measurement:

Morphology: Morphology refers to the shape of the waveform. The shape of a wave or an EEG pattern is determined by the frequencies that combine to make up the waveform and by their phase and voltage relationships. Wave patterns can be described as being:

- **Monomorphic.** Distinct EEG activity appearing to be composed of one dominant activity
- **Polymorphic.** Distinct EEG activity composed of multiple frequencies that combine to form a complex waveform.
- **Sinusoidal.** Waves resembling sine waves. Monomorphic activity usually is sinusoidal.
- **Transient.** An isolated wave or pattern that is distinctly different from background activity.
 - **Spike:** a transient with a pointed peak and duration from 20 to less than 70 msec.
 - **Sharp wave:** a transient with a pointed peak and duration of 70-200 msec.

Variables used in EEG measurement:

Synchrony:

- Synchrony refers to the simultaneous appearance of rhythmic or morphologically distinct patterns over different regions of the head, either on the same side (unilateral) or both sides (bilateral).

Periodicity:

- Periodicity refers to the distribution of patterns or elements in time (e.g., the appearance of a particular EEG activity at more or less regular intervals). The activity may be generalized, focal or lateralized.

Thank You!



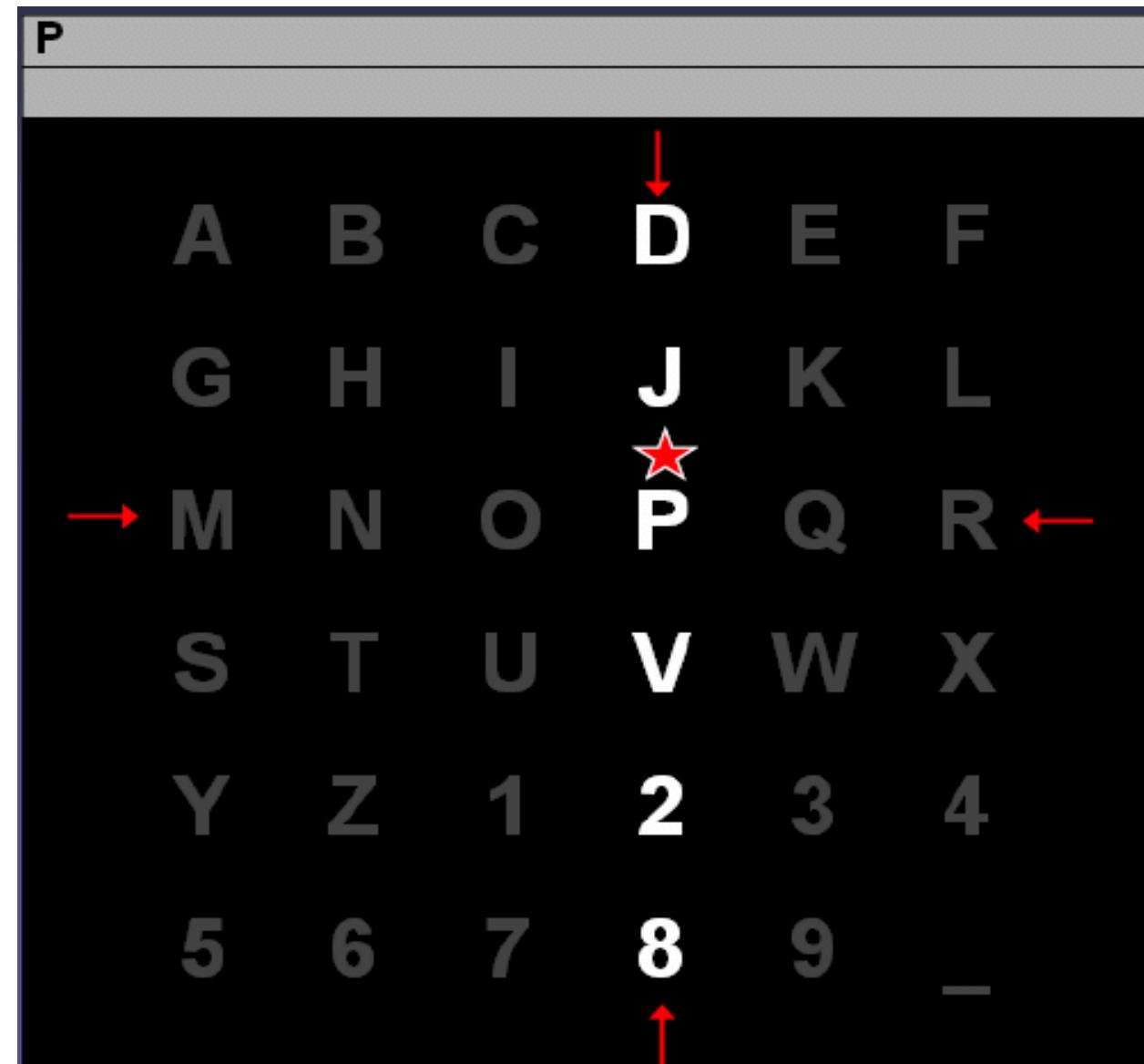
EEG Artifacts

Course Instructors

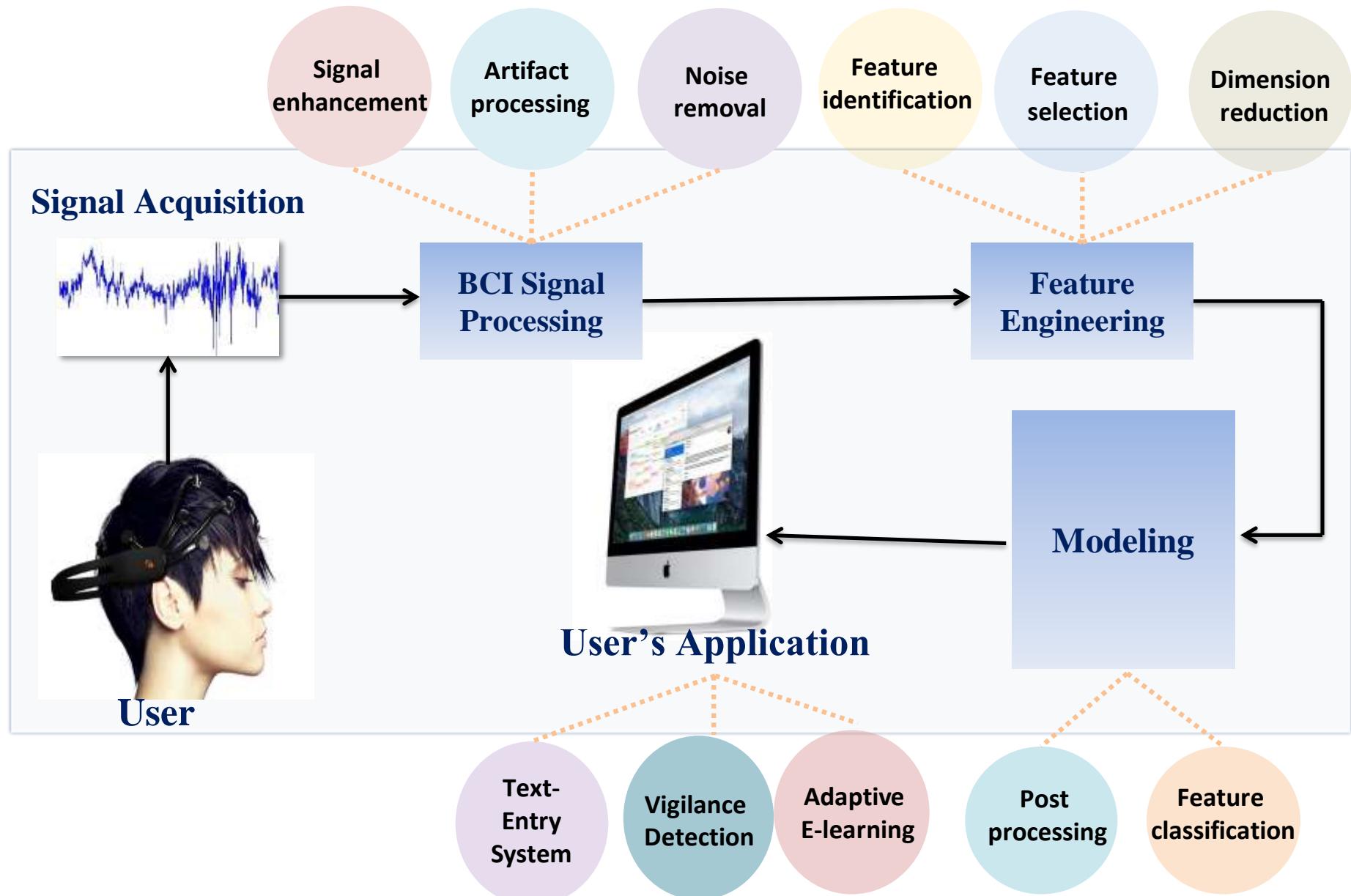
Dr. Annushree Bablani

Acknowledgments: Dr. Sreeja S R

EEG Paradigms



EEG based BCI System Development



Recording the EEG

- **EEG electrodes:**
 - Small metal discs usually made of stainless steel, tin, gold or silver covered with a silver chloride coating.
 - They are placed on the scalp in spatial positions using the International 10/20 system.



Fig: EEG cables showing the disc electrodes to which electrode gel is applied and applied to the subject's scalp.

Recording the EEG

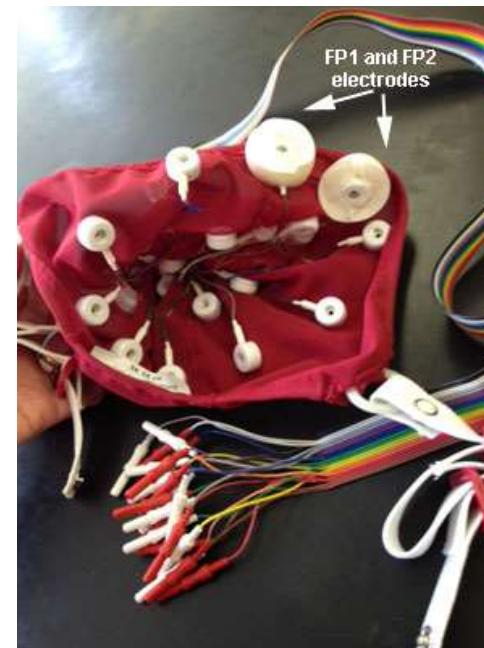
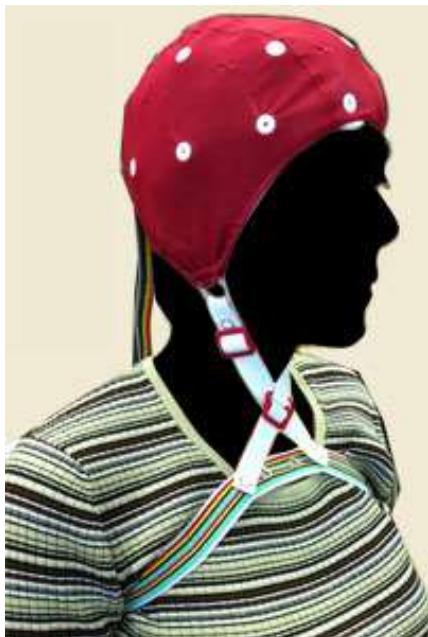


Fig: Many recording systems use a cap into which electrodes are embedded; this facilitates recordings when high density arrays of electrodes are needed or when comparing recording sites. The image to the right shows the inside of such a cap.

Recording the EEG

- **Electrode gel:**

- It acts as a malleable extension of the electrode, so that the movement of the electrodes cables is less likely to produce artifacts.
- The gel maximizes skin contact and allows for a low-resistance recording through the skin.

- **Impedance**

- A measure of the impediment to the flow of alternating current, measured in ohms at a given frequency.
- Larger numbers mean higher resistance to current flow.
- The higher the impedance of the electrode, the smaller the amplitude of the EEG signal.
- In EEG studies, should be at least 100 ohms or less and no more than 5 kohm.

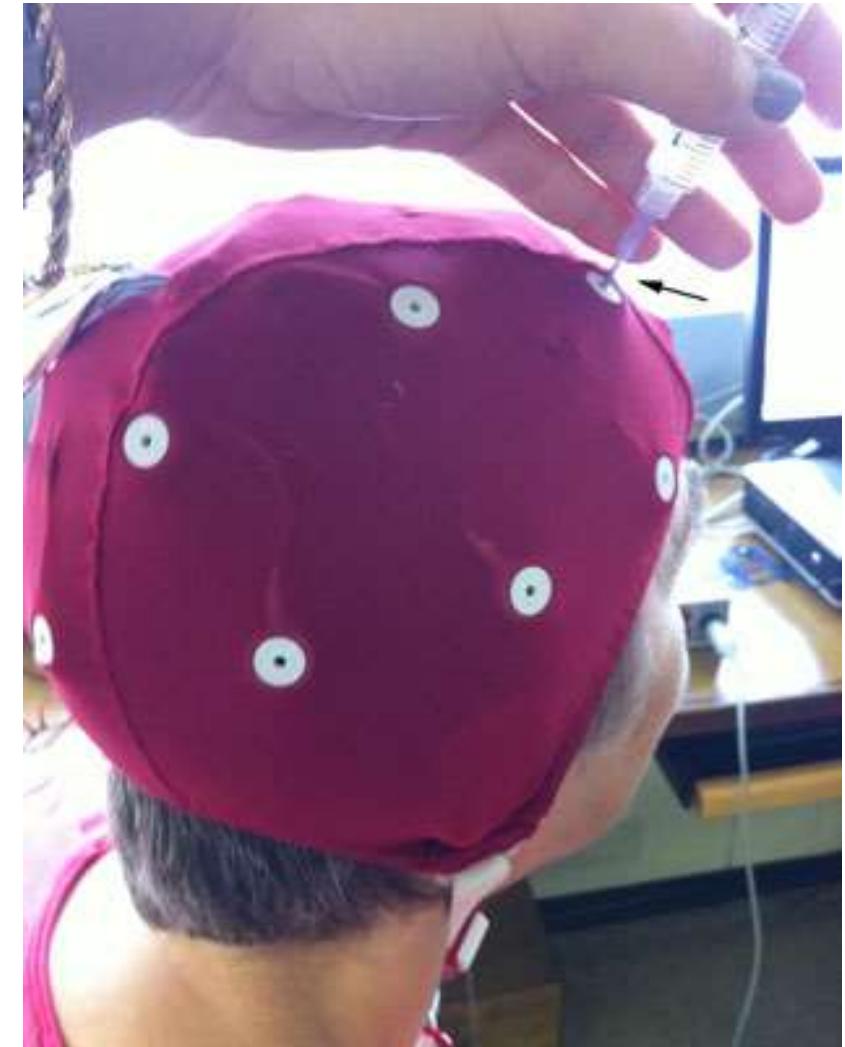


Fig: The electrolytic gel is injected into each cavity until a small amount comes out the hole in the mount. With a moderate amount of downward pressure, the syringe with a blunt needle is rapidly rocked back and forth.

EEG Artifacts

- The electrical artifacts that is not of cerebral origin.
- Anything that is NOT of cerebral origin is termed as **ARTIFACT**
- Physiological and Electrophysiological artifacts.
- Physiological – source (generated other than brain ie. Body)
- Electrophysiological – arise outside the body - equipment and environment
- Some readily distinguished, others closely resemble cerebral activity.

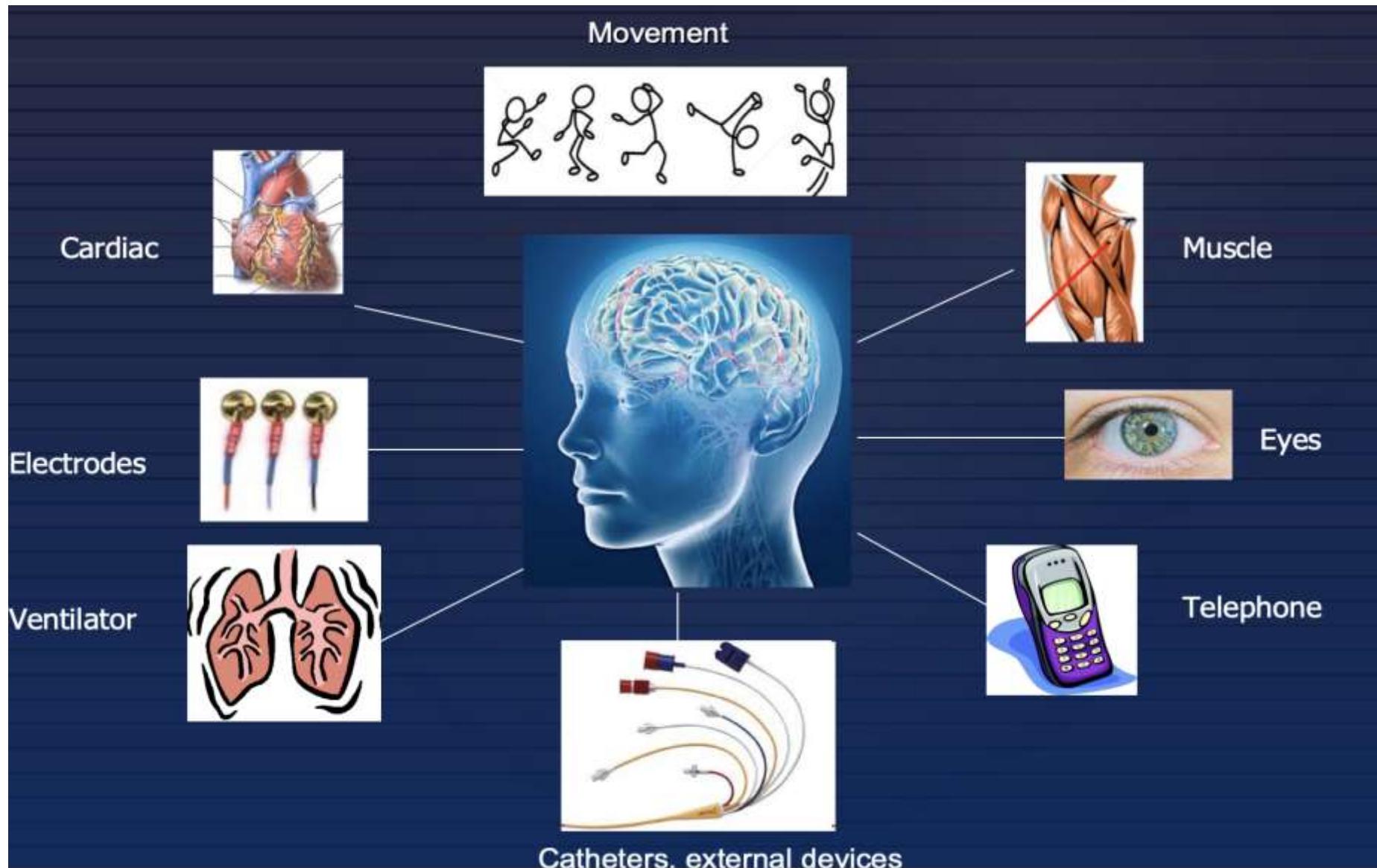
Principles to discriminate artifacts from EEG signals

- Physiological activity has a logical topographic field of distribution with an expected fall of the voltage potentials
- Artifact have an illogical distribution that defies the principles of localization

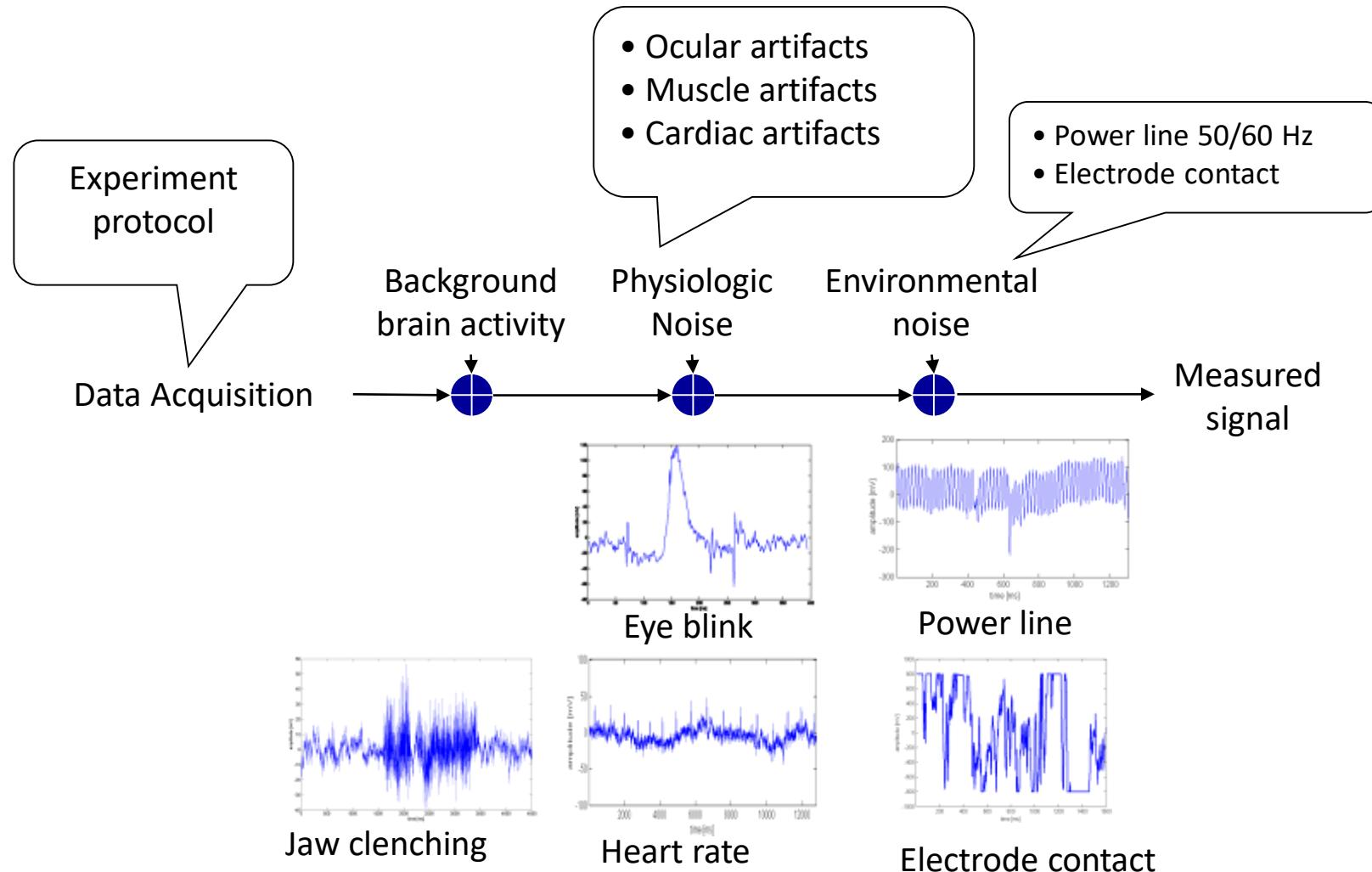
KEY TO AN ARTIFACT FREE RECORDING

- Good, clean preparation
- Good hook-up, neatly bundled electrodes
- Place jack-box close to patients head
- Keep the subject cool, not cold
- Unplug all electrical items close to patient, i.e. bed, radio, fan, etc.

EEG Artifacts

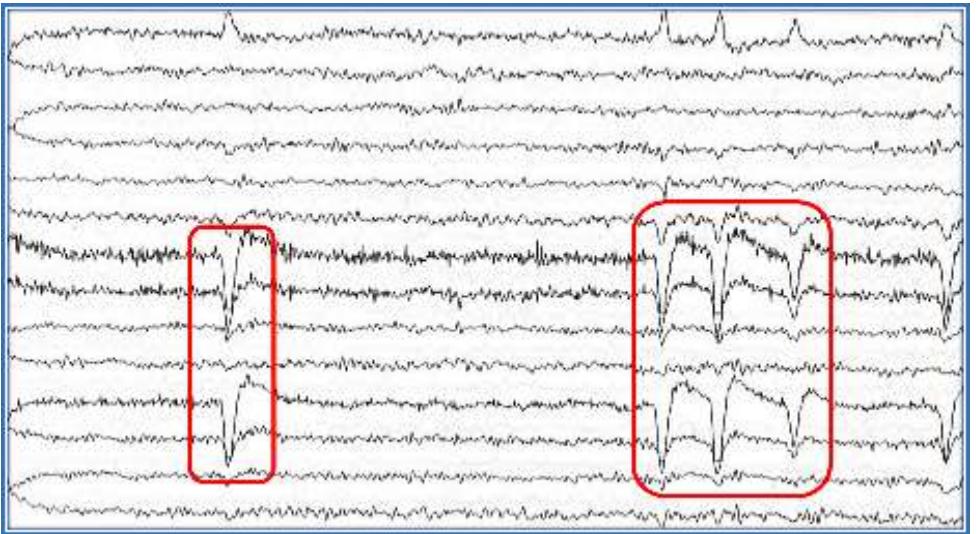


Captured EEG Signal

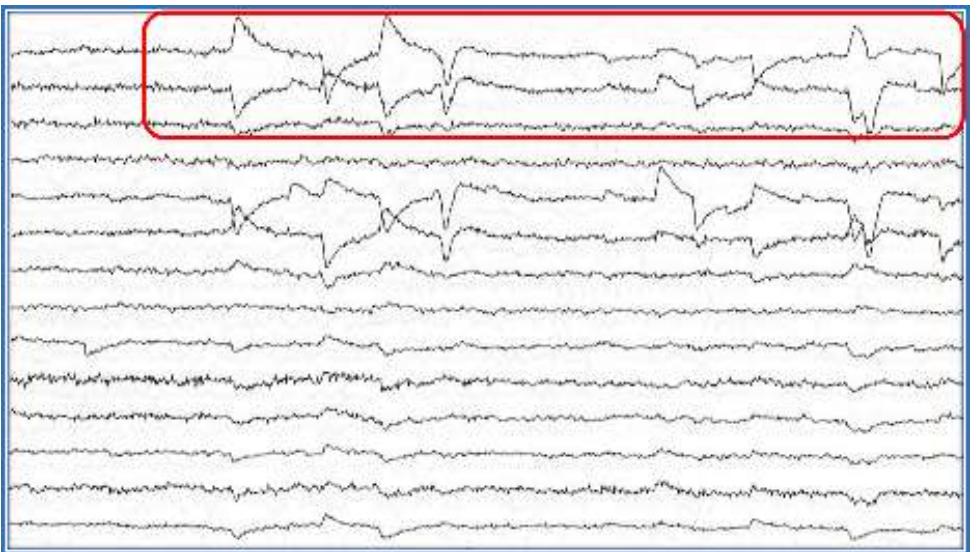


Ocular Artifacts

- Blinks
- Eye flutter
- Lateral gaze
- Slow/roving eye movement
- Rapid eye movement
- Electroretinogram (ERG)



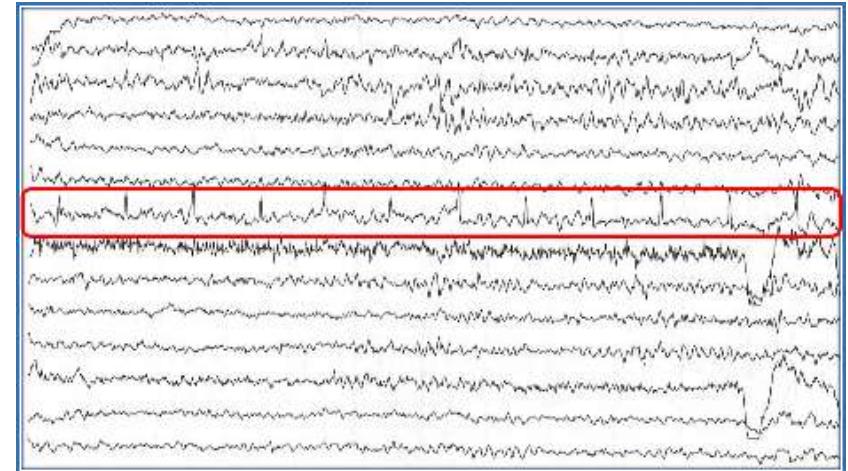
Blink



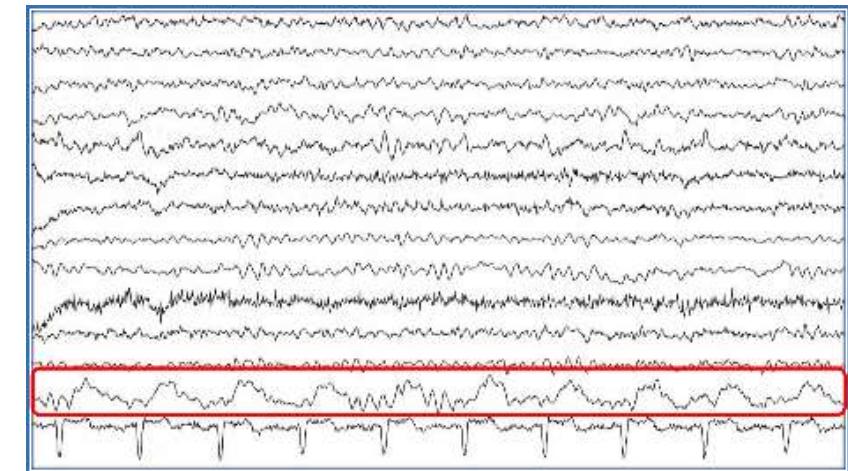
Lateral Eye Movement

Cardiac Artifacts

- Mechanical and Electrical
- ECG, Pacemaker - Electrical
- Pulse, Ballistocardiographic – Mechanical
- ✓ Mostly these are high in amplitude and prominent in babies, obese and short neck persons.
- ✓ Referential montages picks up cardiac artifacts.



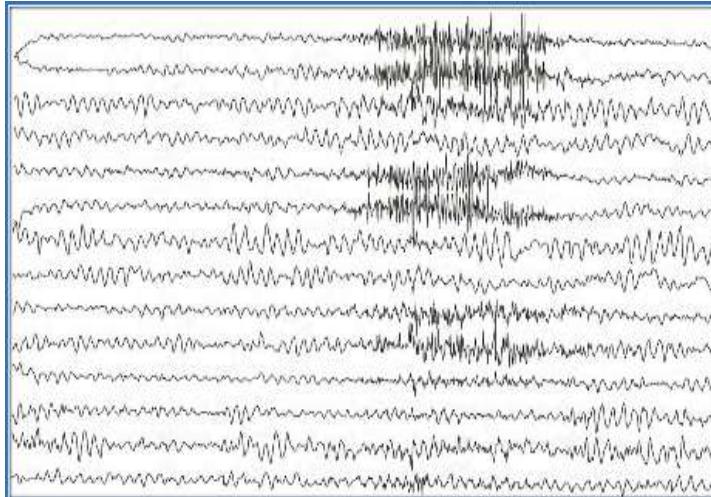
Cardiac (Electrical)



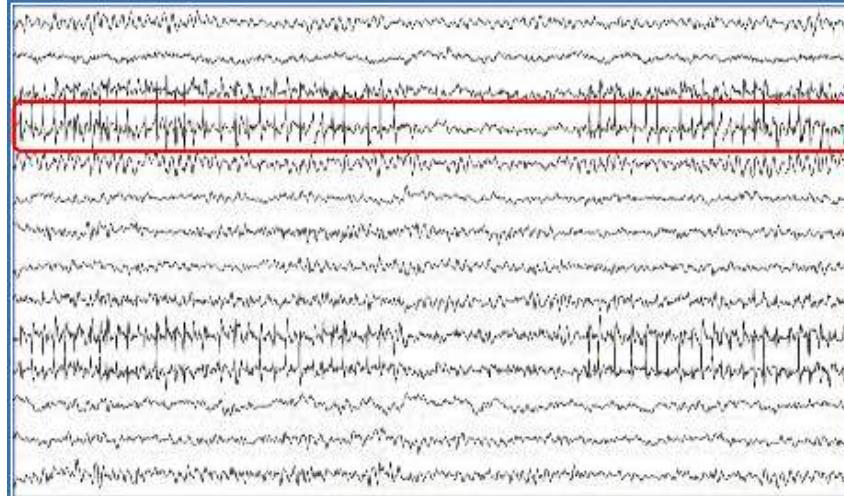
Cardiac (Mechanical)

Muscle Artifacts

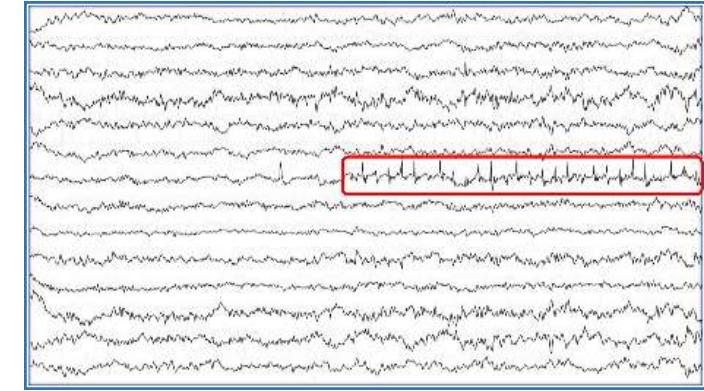
- ✓ Glossokenetic (related to tongue movements, Chew and swallow)
- ✓ Photomyogenic/ Photo-myoclonic (When flash of light falls over the face, the activity occurs due to myoclonus of the facial muscles).
- ✓ Surface EMG (Electromyography) – used to measure electrical activity during muscle contractions and relaxation cycles.



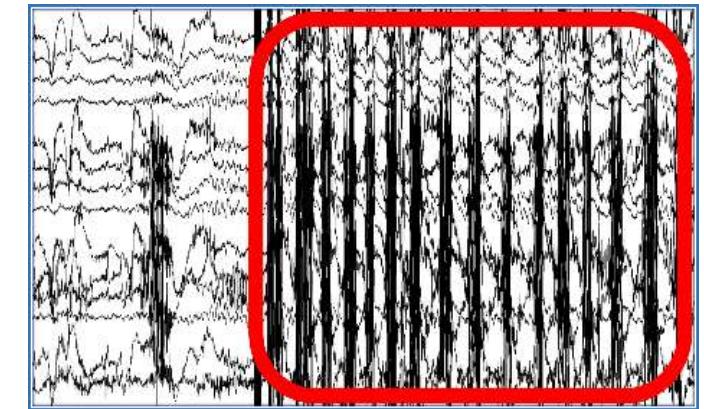
Electromyography (Scalp)



Electromyography (Facial)



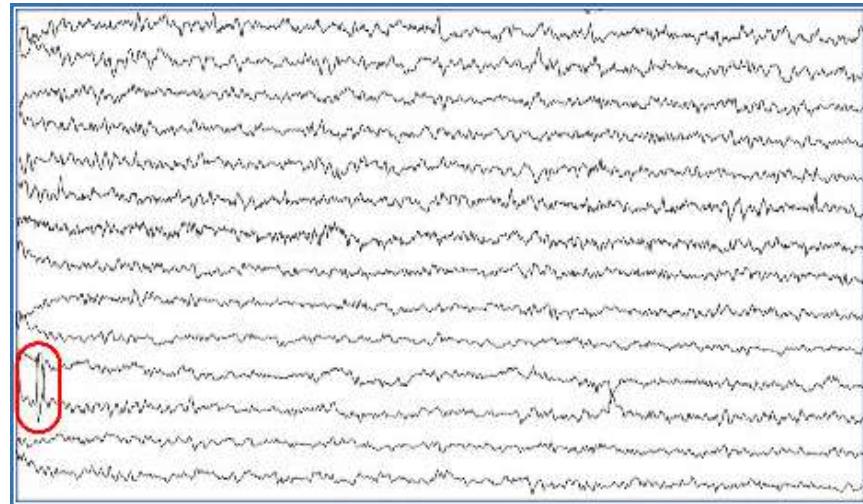
Photomyogenic



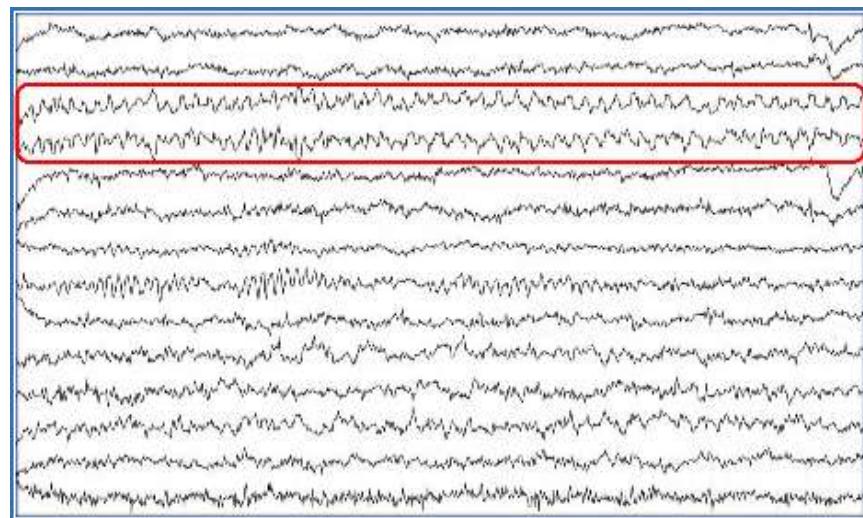
Chewing

Electrode and Equipment Artifacts

- ✓ Electrode pop, electrode contact, electrode movement
- ✓ Perspiration – the process of sweating
- ✓ salt bridge – differs from perspiration by low amplitude.
- ✓ Movement artifacts - Movement of head, body and limbs produce irregular high voltage potentials
- ✓ 50/60 Hz ambient electrical noise.
- ✓ Ventilators, circulatory pumps.
- ✓ Telephone, mobile.



Electrode Pop



Electrode Movement

Electrode and Equipment Artifacts

- Seen due to smearing of the electrode paste between electrodes or presence of perspiration across the scalp
- Forms an unwanted electrical connection between the electrodes forming a channel

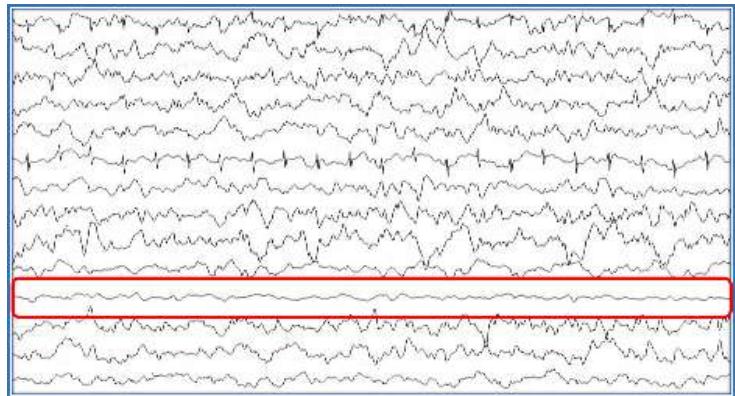
✓ Perspiration artifact

- manifests as low amplitude
- undulating (smooth) waves
- duration is typically greater than 2 sec

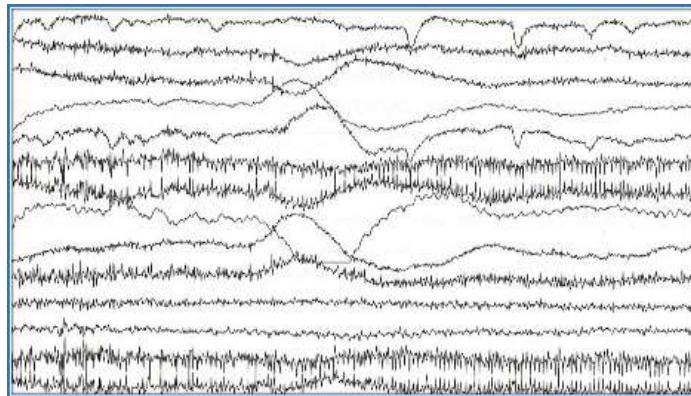
✓ Slat bridge artifact

- lower in amplitude
- not wavering with low frequency oscillation - typically include only one channel
- It may appear flat and close to isoelectric

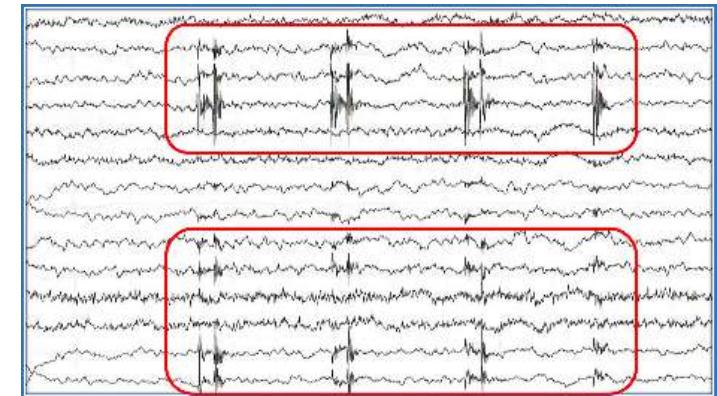
Electrode and Equipment Artifacts



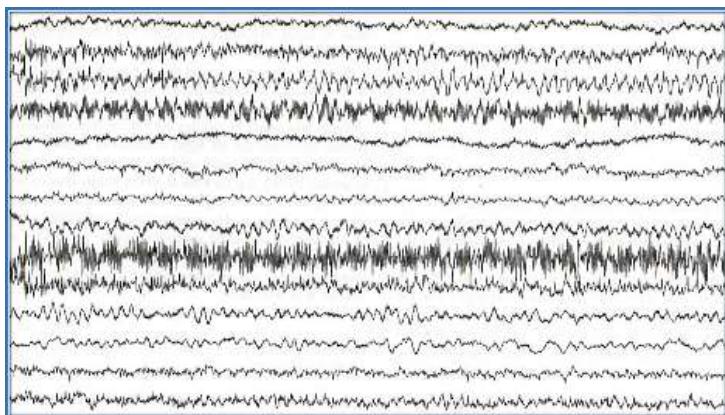
Salt Bridge



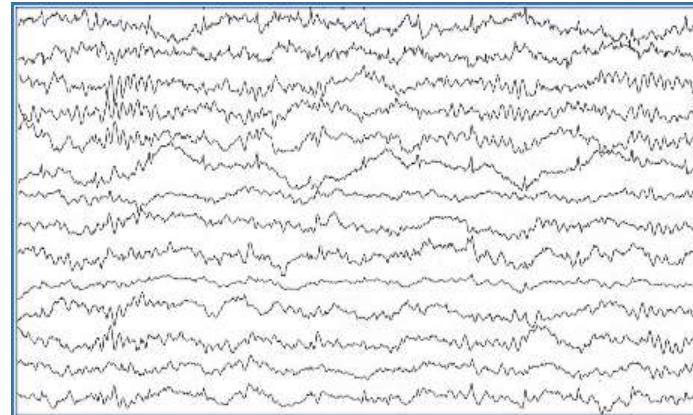
Electrode Lead Movement



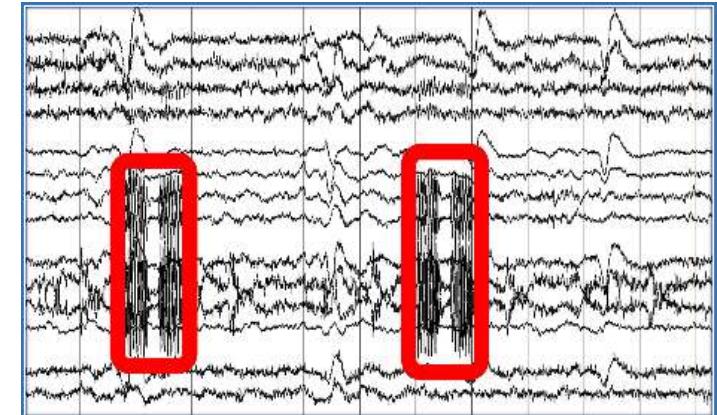
Electrical Motor



60 Hz



Perspiration



Phone

Thank You!

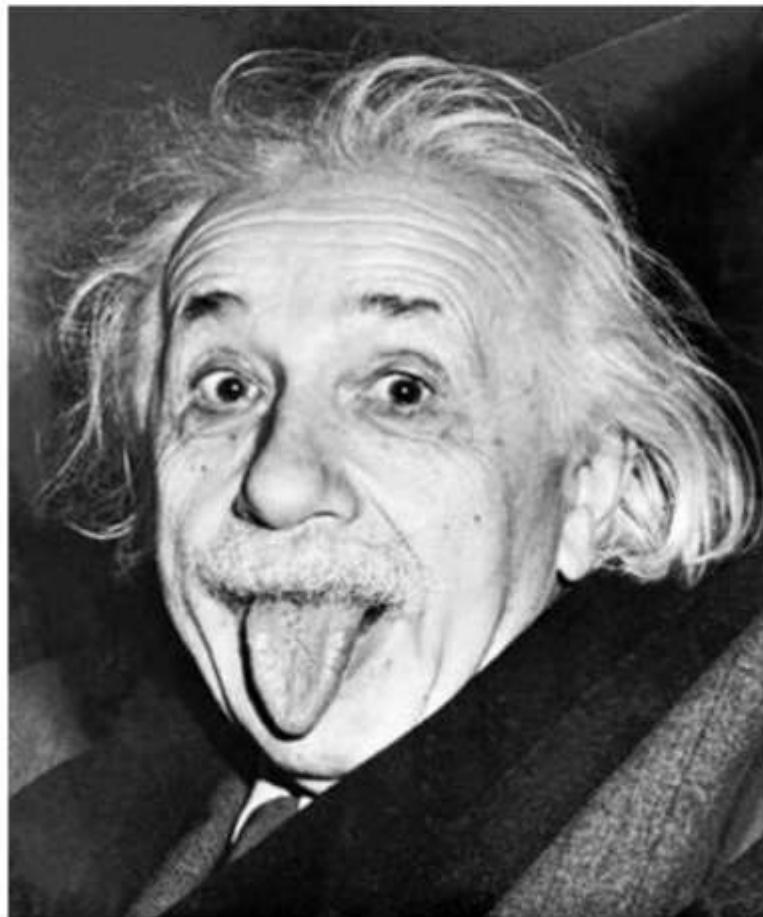


EEG Signal Pre-processing - Epoching

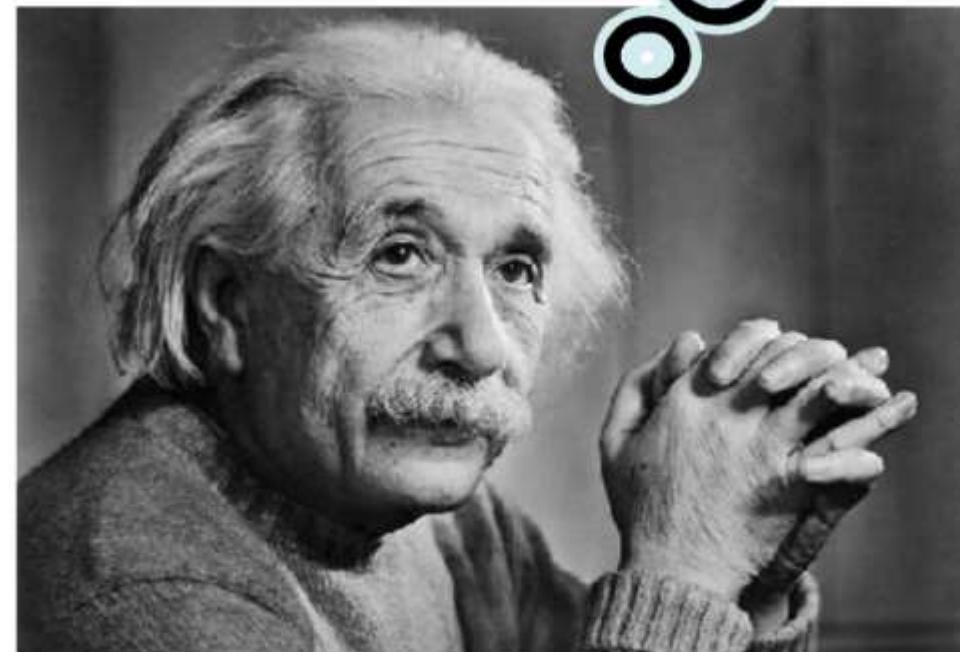
Course Instructor

Dr. Annushree Bablani

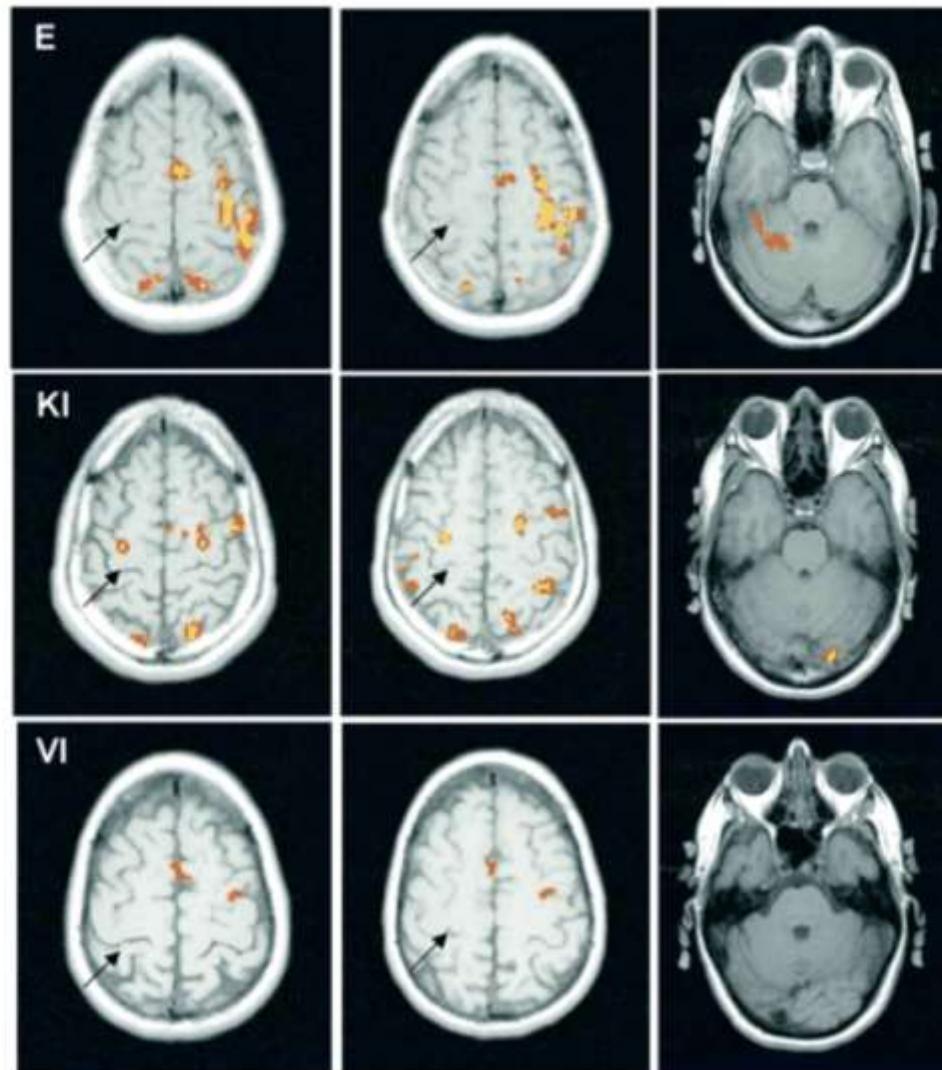
Motor Imagery



VS

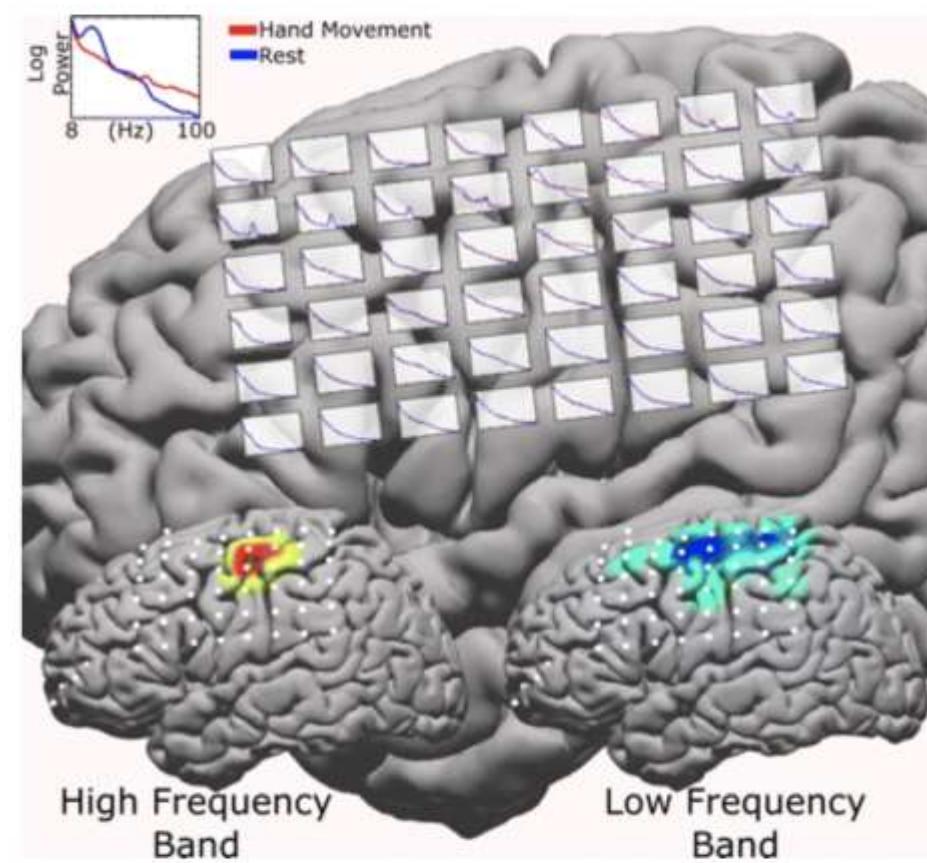
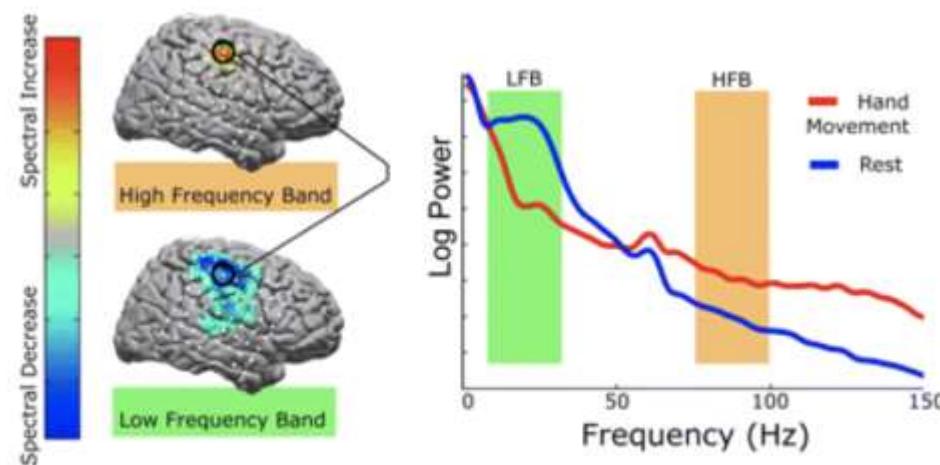
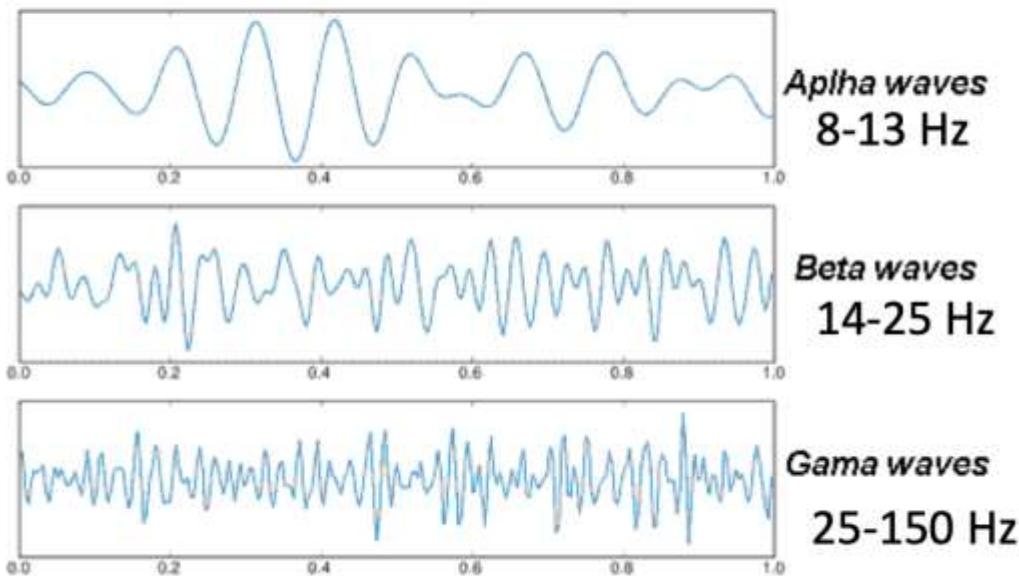


Brain activity during motor action vs imagery



Solodkin et al, 2004

Motor rhythms in cortex



Miller et al, 2007

Goal of the work

To check whether real movements can be compared with imagery movements.

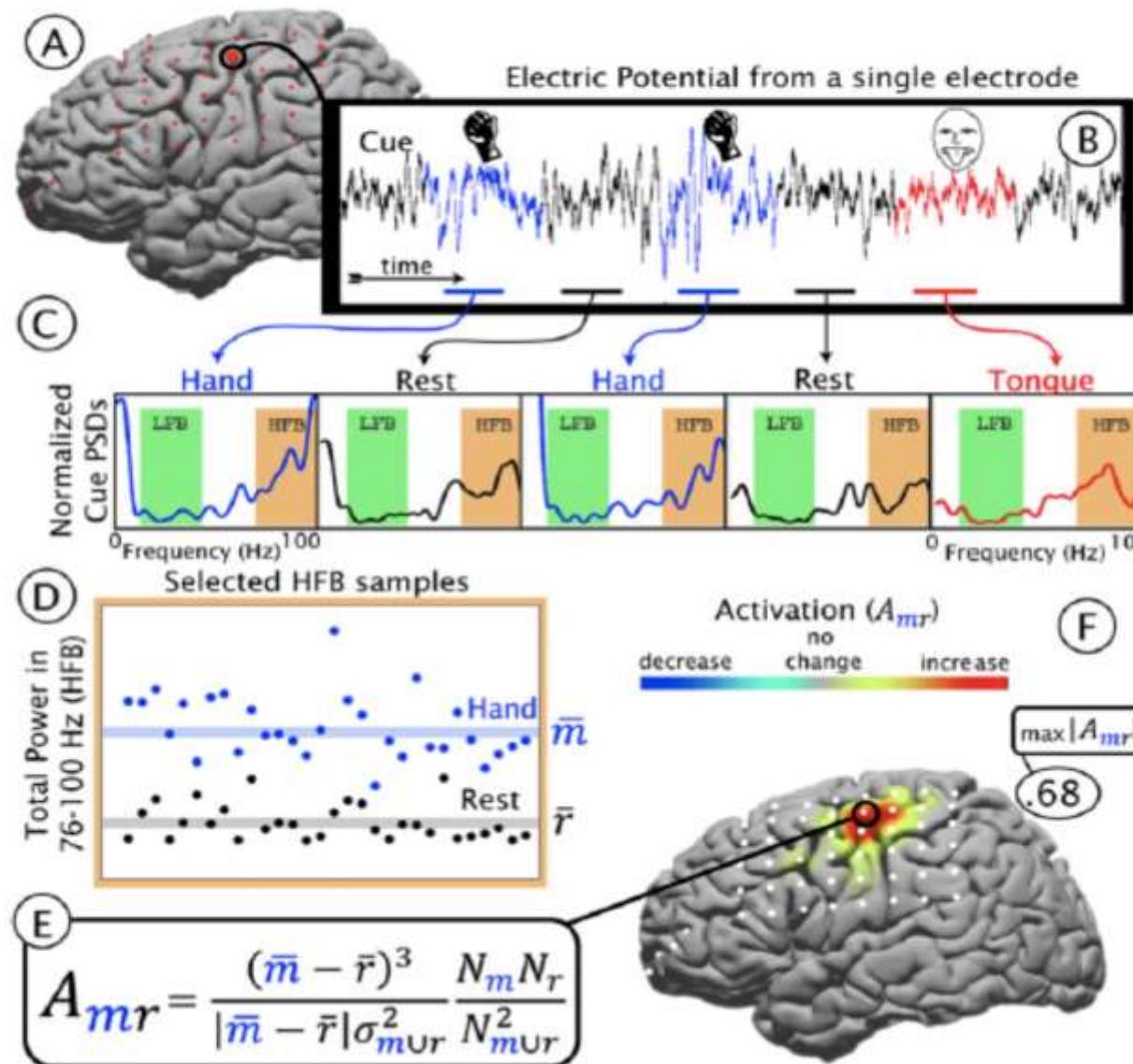
Methods Used:

- 8 patients implanted with 4x8 or 8x8 grid

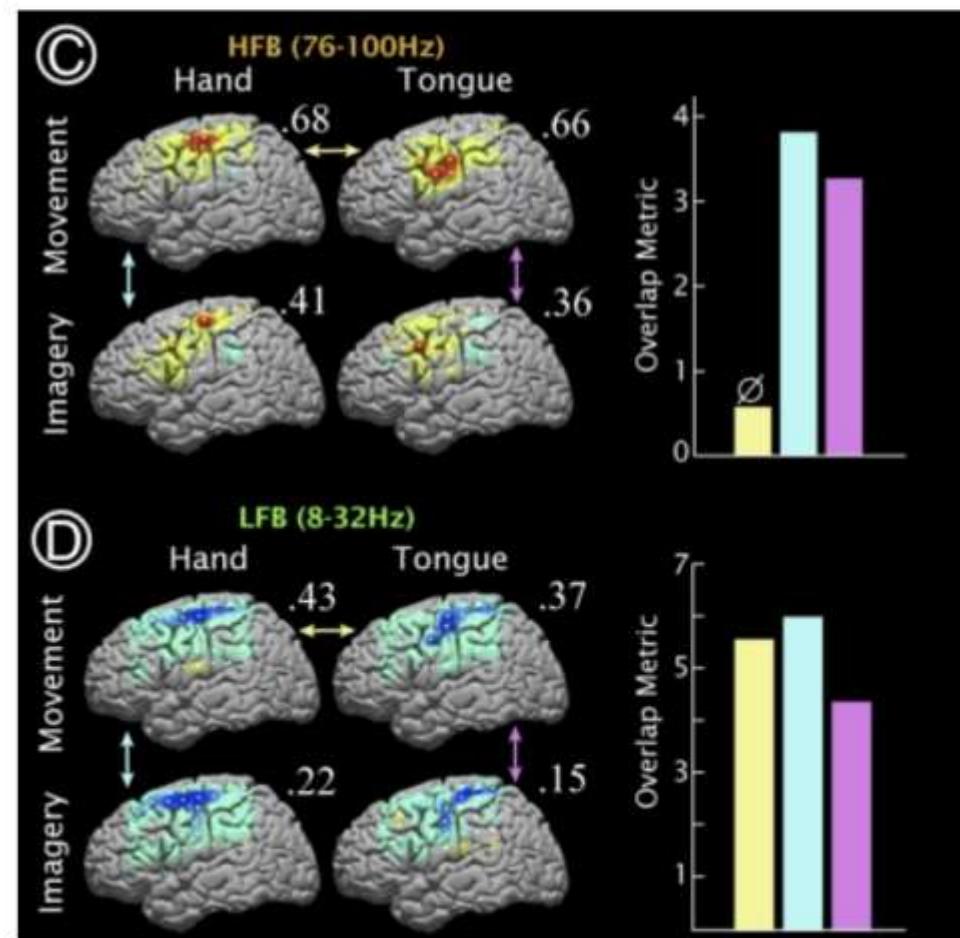
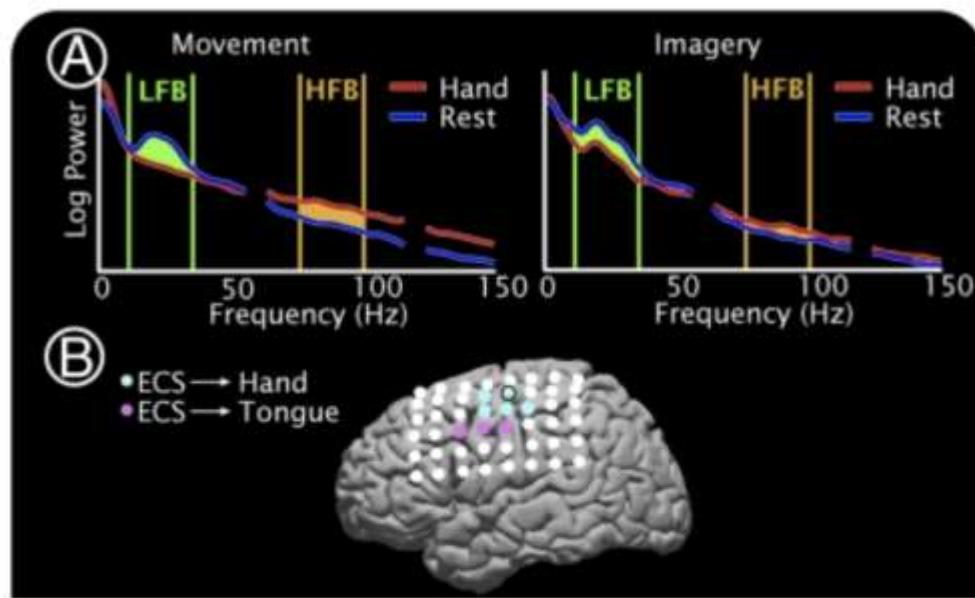
1) Active movements –clench – release of hand, stick out tongue, shoulder shrug, say the word “move”

2) Image movements – same as before

Quantification of brain activity



Cortical activity during real and imagined movements



Data Epoching

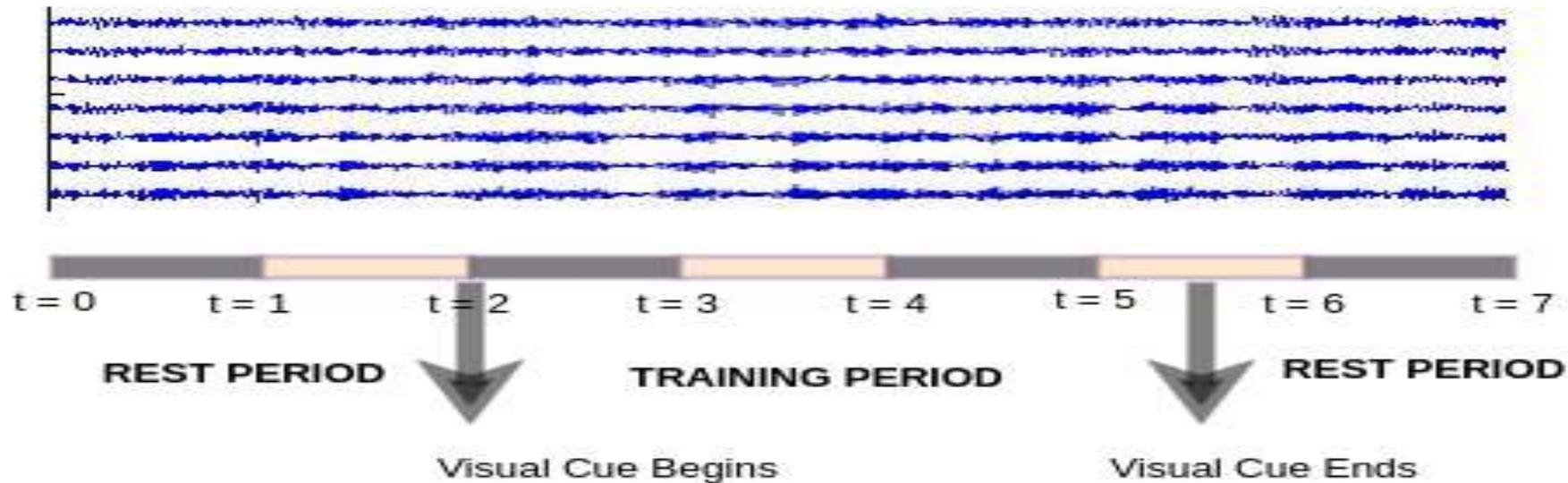
Selecting data epochs

There is no real good reason to select subsets of data epochs. When comparing conditions – performed by creating contrast at the STUDY level (the group analysis interface which may also be used for single-subject analysis) – one may ignore specific data epochs.

- Non-overlapping segments
- Overlapping segments
 - Fully overlapping segments
 - Partially overlapping segments

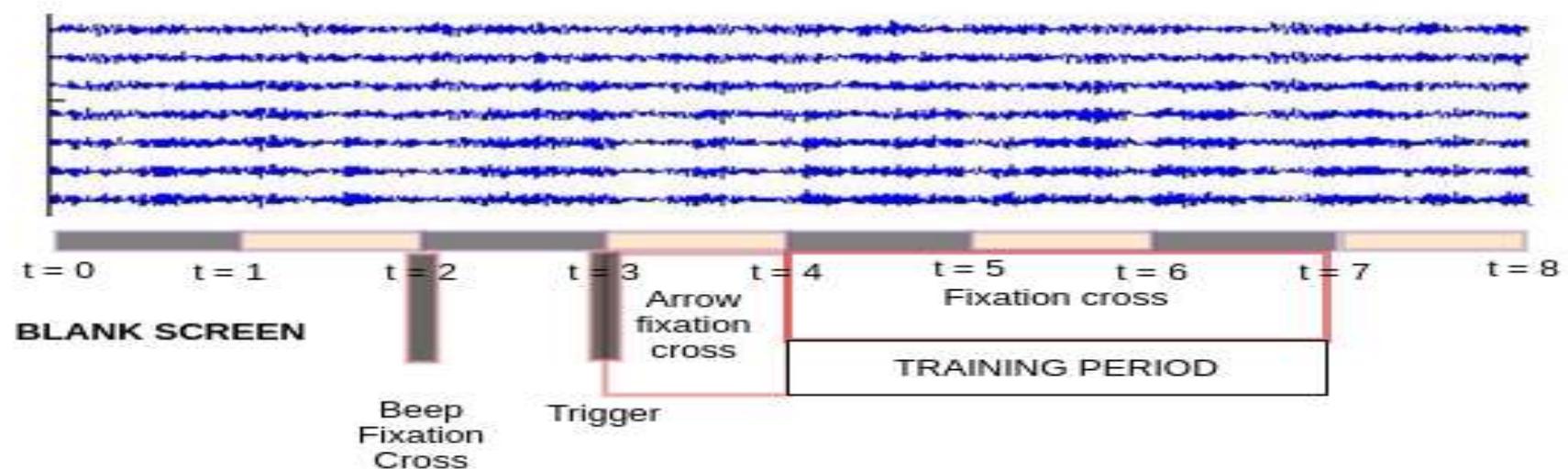
DATASET 1 SINGLE TRIAL

Class : Right hand / Foot

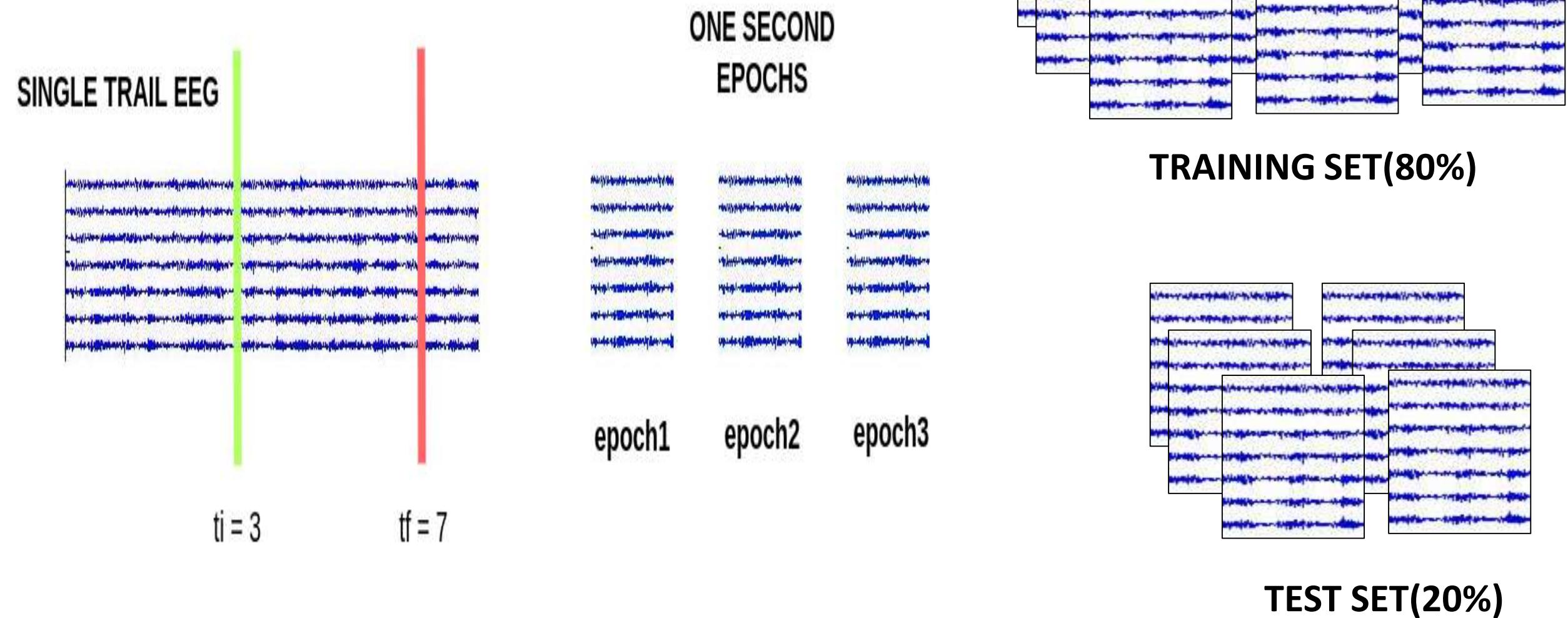


DATASET 2 SINGLE TRIAL

Class : Right hand / Left hand / Foot / Tongue



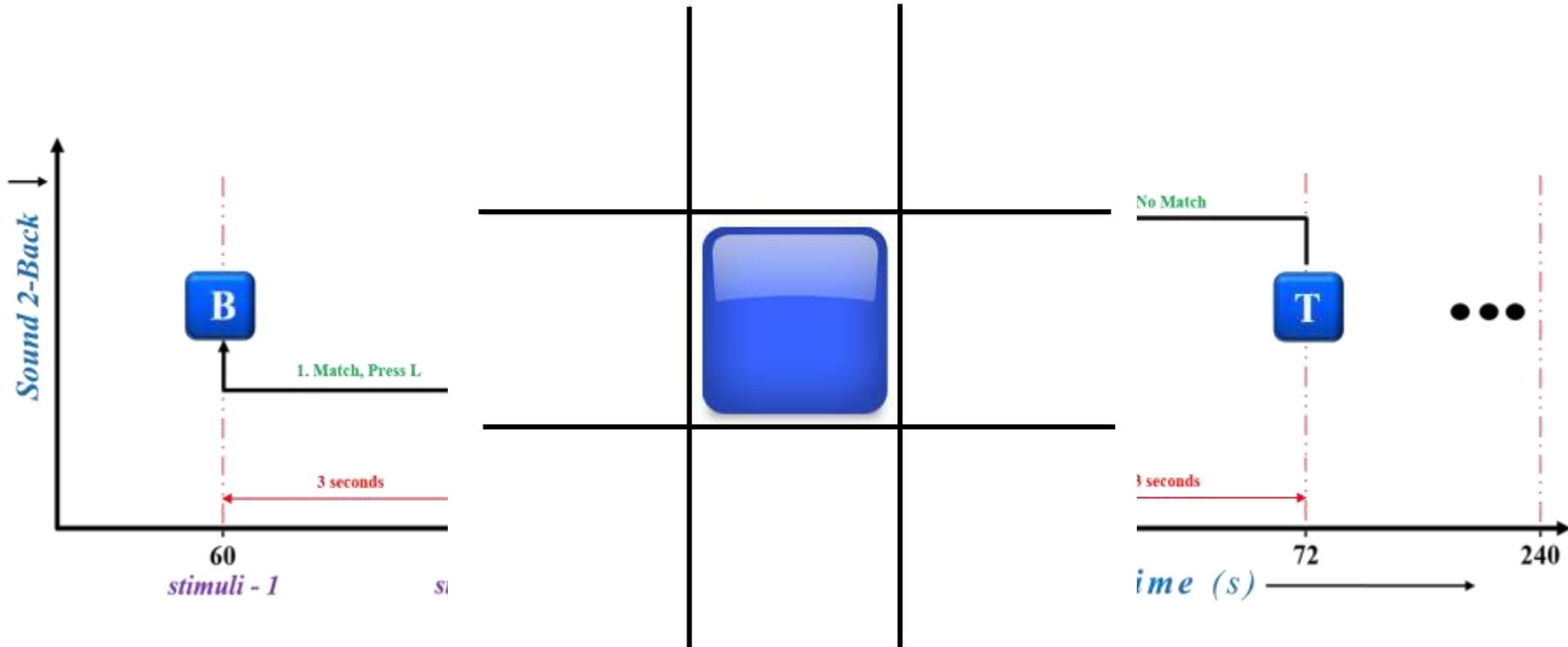
Data Epoching



Cognitive Workload

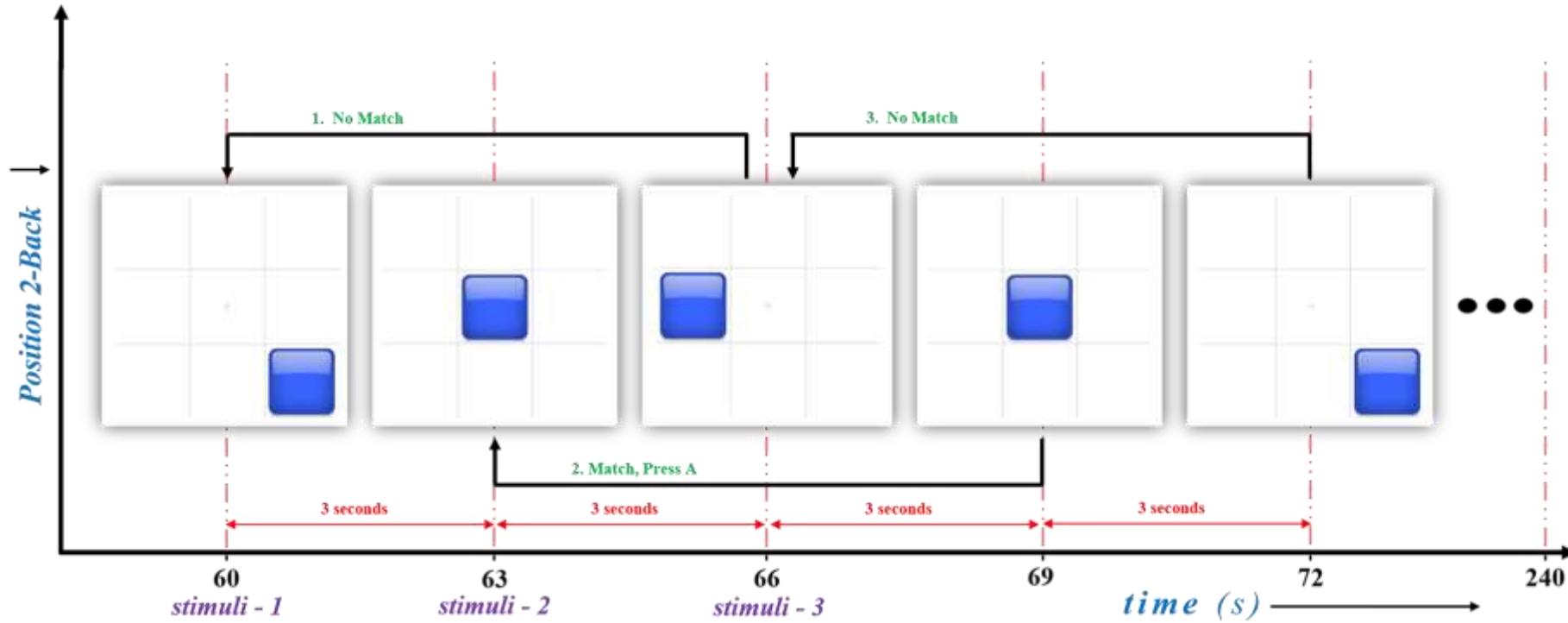
- Cognitive Workload (**CWL**) is a demand placed upon humans for mental resources while performing a task.
- Mental resources include working memory, ability to process, etc.
- **Working memory (WM)** is a cognitive system with a limited capacity to hold a small amount of information and process it.

n-Back Task



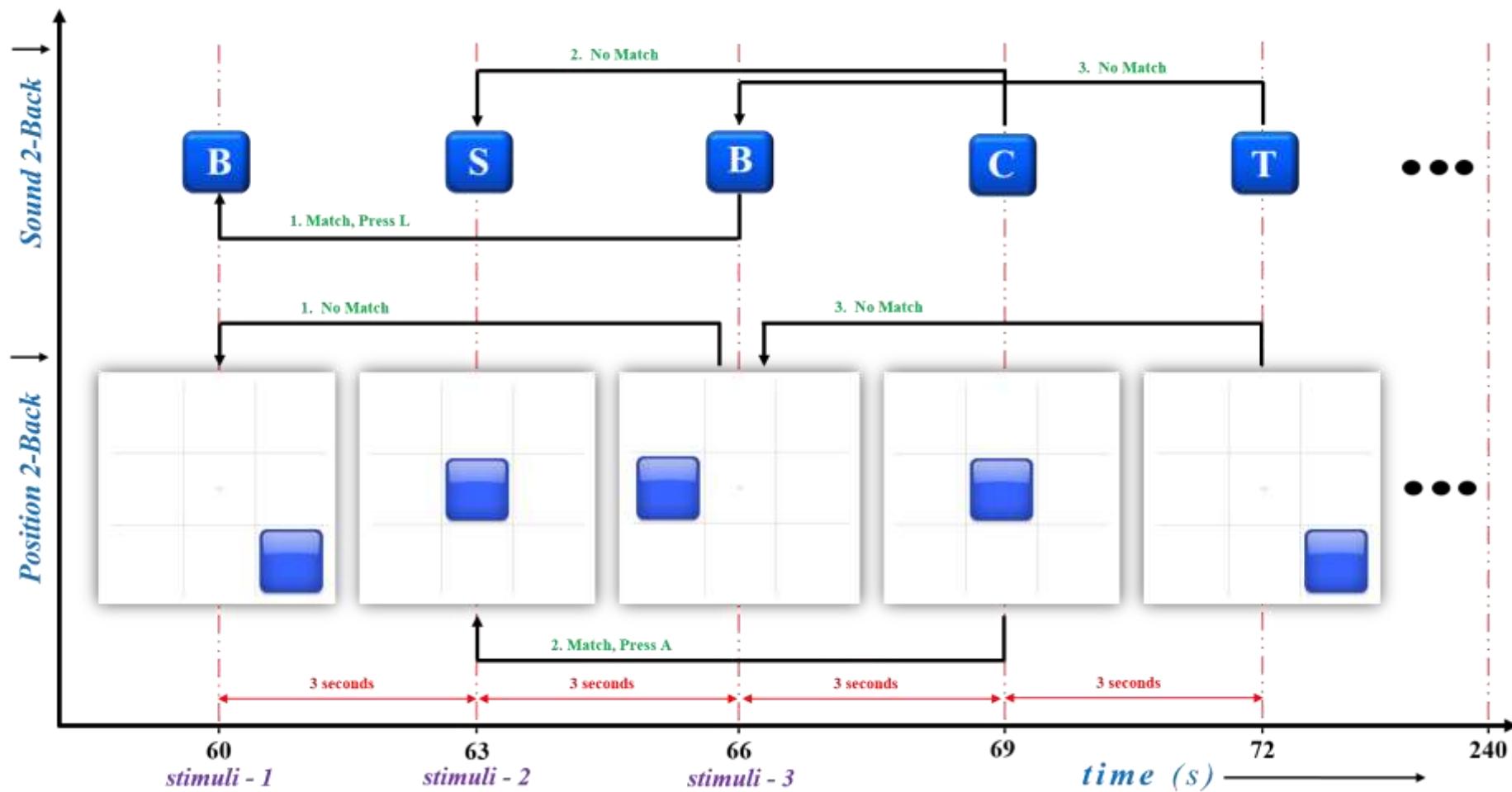
Sound 2-Back

n-Back Task



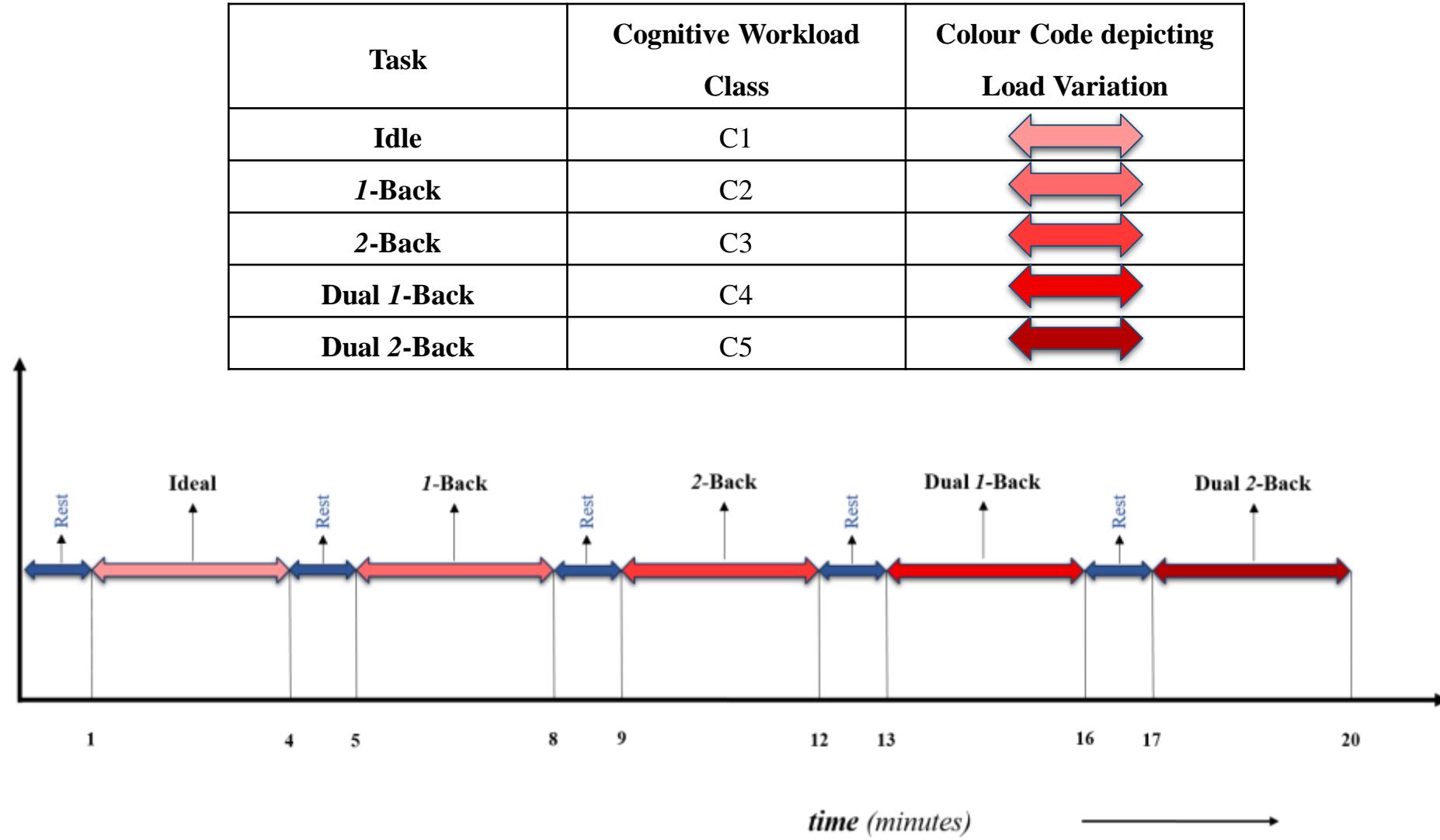
Position 2-Back

n-Back Task



Sound & Position 2-Back

Data Epoching



Thank you!!

Signal Processing

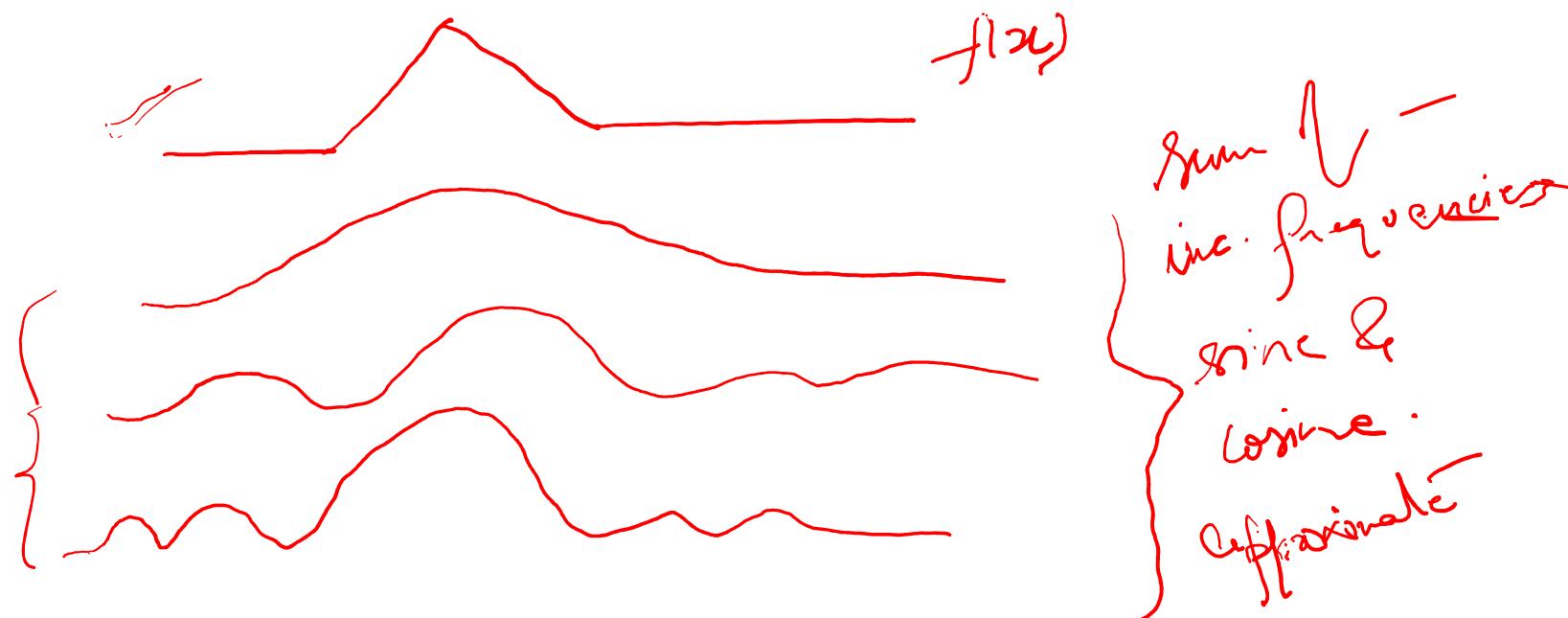
Frequency Domain Analysis

Frequency Domain Analysis

- EEG signals are recorded in the domain of **TIME**.
- Introduced by J.-B. Joseph Fourier in the early 1800s
- It's a coordinate transform system
- Fourier introduced the concept that sine and cosine functions of increasing frequency provide an orthogonal basis for the space of solution functions.

Fourier Series

- Any arbitrary function can be represented using sine and cosines.
- Sine and cosine form the basis of the function space.

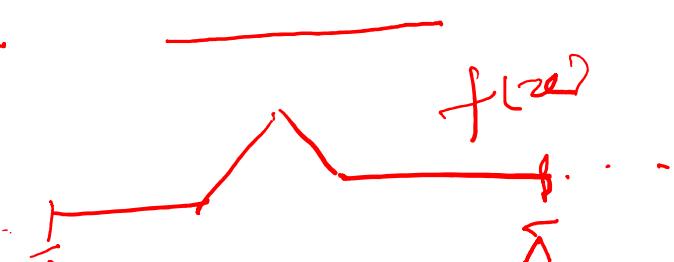


Fourier Series

- Approximating arbitrary function $f(x)$, as a infinite sum of sine and cosine of increasing high frequency.

$$f(x) = \frac{A_0}{2} + \sum_{k=1}^{\infty} [A_k \cos(kx) + B_k \sin(kx)]$$

Where A_k & B_k are Fourier constants



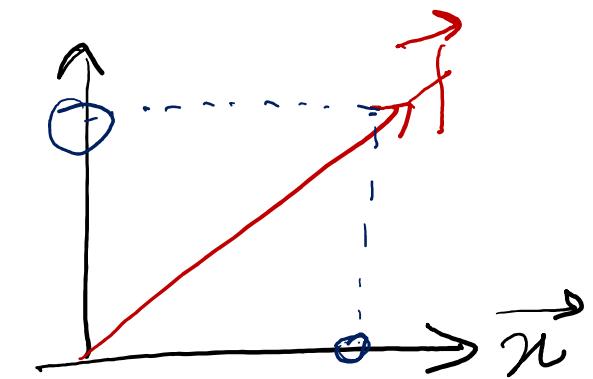
$$A_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(kx) dx = \frac{1}{\|\cos(kx)\|^2} \langle f(x), \cos(kx) \rangle$$

$$B_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cdot \sin(kx) dx = \frac{1}{\|\sin(kx)\|^2} \langle f(x), \sin(kx) \rangle$$

Fourier Series

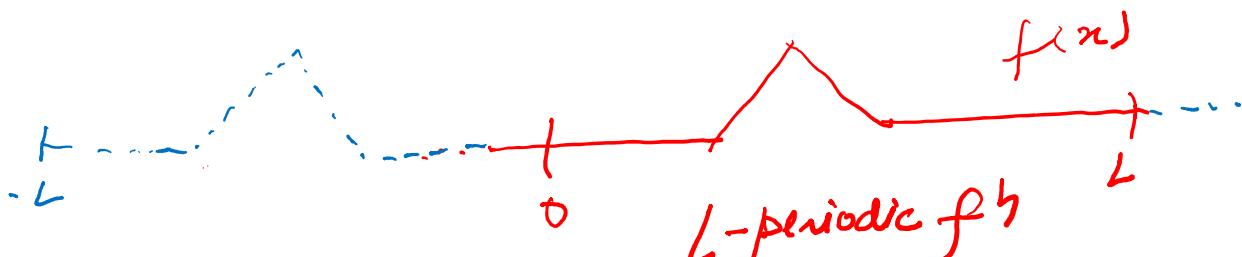
$$\vec{f} = \underbrace{\langle \vec{f}, \vec{x} \rangle}_{= \vec{y}} \cdot \frac{\vec{x}}{\|\vec{x}\|^2} + \langle \vec{f}, \vec{y} \rangle \cdot \frac{\vec{y}}{\|\vec{y}\|^2}$$

$$f(x) = \underbrace{f(x) \cdot \cos(kx)}_{\|f(x)\|} \cdot \frac{\cos kx}{\|\sin kx\|^2} + \text{flr. sin(kx)} \frac{\sin kx}{\|\sin kx\|^2}$$



$\rightarrow f^n$ space

Fourier Series



$$f(x) = \frac{A_0}{2} + \sum_{k=1}^{\infty} \left(A_k \cos\left(\frac{2\pi k x}{L}\right) + B_k \sin\left(\frac{2\pi k x}{L}\right) \right)$$

$$A_k = \frac{2}{L} \int_0^L f(x) \cdot \cos\left(\frac{2\pi k x}{L}\right) dx$$

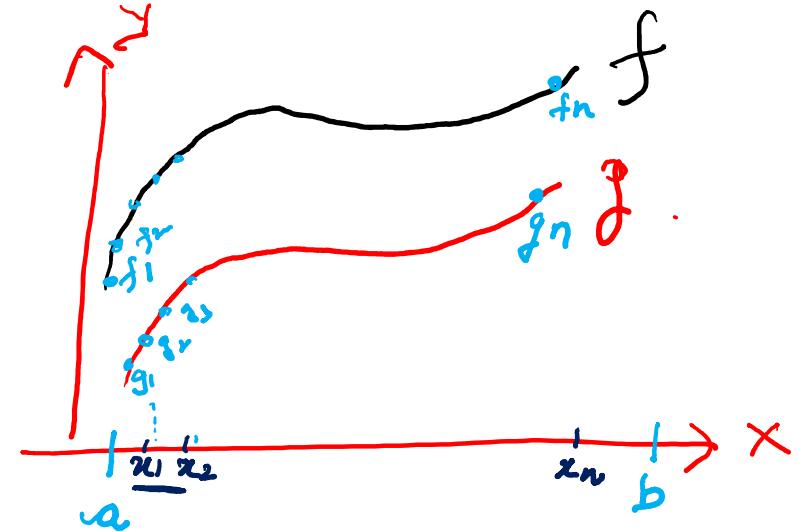
$$B_k = \frac{2}{L} \int_0^L f(x) \cdot \sin\left(\frac{2\pi k x}{L}\right) dx$$

Inner Product of Functions

$$f = [f_1 \ f_2 \ \dots \ f_n]^T$$

$$g = [g_1 \ g_2 \ \dots \ g_m]^T$$

$$\langle f(x), g(x) \rangle = \int_a^b f(x) g(x) dx$$



$$\Delta x = \frac{b-a}{n-1}$$

When 'n' data points are increasing

$$\frac{b-a}{n-1} \langle f, g \rangle = \sum_{k=1}^n f(x_k) g(x_k) \cdot \Delta x$$

$$n \rightarrow \infty \equiv \Delta x \rightarrow 0$$

Fourier Series for Complex functions

$$f(x) = \sum_{k=-\infty}^{\infty} c_k e^{ikx}$$

$c^{ikx} = \cos(kx) + i \sin(kx)$
 Euler's expansion
 $i = \sqrt{-1}$

$$f(x) = \sum_{k=-\infty}^{\infty} (\alpha_k + i \beta_k) [\cos(kx) + i \sin(kx)]$$

$$= (\alpha_0 + i \beta_0) + \sum_{k=1}^{\infty} \left[(\underline{\alpha_{-k}} + \underline{\alpha_k}) \cos(kx) + (\underline{\beta_{-k}} - \underline{\beta_k}) \sin(kx) \right]$$

$$+ i \sum_{k=1}^{\infty} \left[(\beta_{-k} + \beta_k) \cos(kx) - (\alpha_{-k} - \alpha_k) \sin(kx) \right]$$

$$\text{Let } e^{ikx} = \cos(kx) + \sin(kx) = \psi_k \quad k \in \mathbb{Z}$$

$$\begin{aligned} \langle \psi_j, \psi_k \rangle &= \int_{-\pi}^{\pi} e^{ijx} e^{-ikx} dx = \int_{-\pi}^{\pi} e^{i(j-k)x} dx \\ &= \frac{1}{i(j-k)} \left[e^{i(j-k)x} \right]_{-\pi}^{\pi} = \begin{cases} 0, & \text{if } j \neq k \\ 2\pi, & \text{if } j = k \end{cases} \end{aligned}$$

We can write as

$$\frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \langle f(x), \psi_k \rangle \psi_k$$

$\underbrace{\hspace{10em}}$

ψ_k e^{ikx}

$$\|\psi_k\|^2 = 2\pi$$

③ Fourier Transform is a linear operator

$$\hat{F}(\alpha f(\omega) + \beta g(\omega)) = \alpha \hat{F}(f(\omega)) + \beta \hat{F}(g(\omega))$$

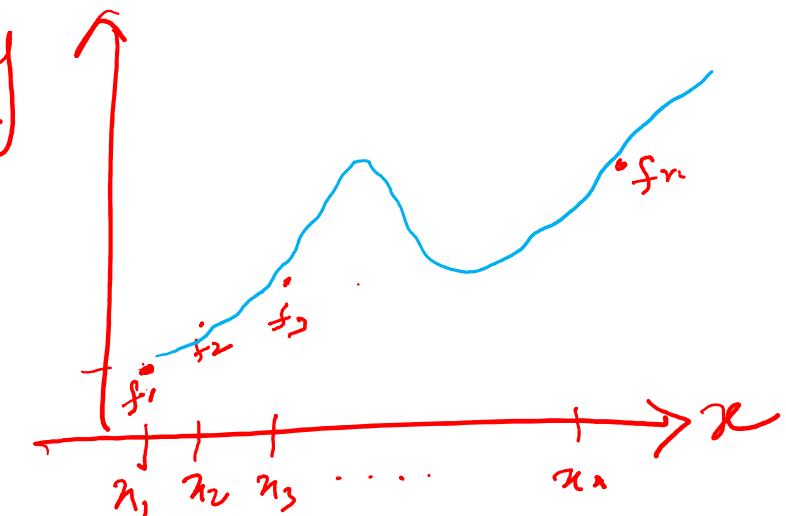
$$F^{-1}(\alpha \hat{f}(\omega) + \beta \hat{g}(\omega)) = \alpha f(\omega) + \beta g(\omega)$$

④ Parseval's theorem

$$\int_{-\infty}^{\infty} |\hat{f}(\omega)|^2 d\omega = 2\pi \int_{-\infty}^{\infty} |f(x)|^2 dx$$

Discrete Fourier Transform

$$\begin{bmatrix} f_0 \\ f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} = \begin{bmatrix} \hat{f}_0 \\ \hat{f}_1 \\ \hat{f}_2 \\ \vdots \\ \hat{f}_n \end{bmatrix}$$



$$\hat{f}_k = \sum_{j=0}^{n-1} f_j e^{-i 2\pi j k / n}$$

$$f_k = \left[\sum_{j=0}^{n-1} \hat{f}_j e^{i 2\pi j k / n} \right] \cdot \frac{1}{n}$$

$\{f_0, f_1, f_2, \dots, f_n\} \xrightarrow{\text{DFT}} \{\hat{f}_0, \hat{f}_1, \dots, \hat{f}_n\}$
 \hat{f}_j : how much of each freq. is required to reconstruct the data in f .

$$f_j e^{-i \omega j k / n} \Rightarrow e^{-i \omega j k / n} \Rightarrow \underline{\omega_n} \rightarrow \text{fundamental freq.}$$

$$\hat{f}_k = \sum_{j=0}^{n-1} f_j e^{-i \omega j k / n}$$

[approximation in form of
sine & cosines with
n discrete values]

$$\begin{bmatrix} \hat{f}_0 \\ \hat{f}_1 \\ \vdots \\ \hat{f}_n \end{bmatrix} \xrightarrow{k} \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & \omega_n & \omega_n^2 & \cdots & \omega_n^{n-1} \\ 1 & \omega_n^2 & \omega_n^4 & \cdots & \omega_n^{2(n-1)} \\ \vdots & & & & \vdots \\ 1 & \omega_n^{n-1} & \omega_n^{e(n-1)} & \cdots & \omega_n^{(n-1)^2} \end{bmatrix} \begin{bmatrix} f_0 \\ f_1 \\ \vdots \\ f_n \end{bmatrix}$$

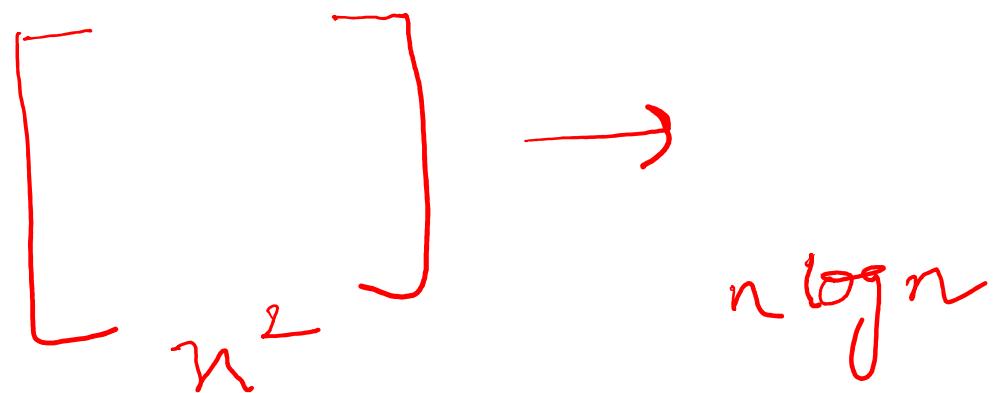
DFT \rightarrow Mathematical Transform

FFT \rightarrow computationally efficient way of computing DFT

FAST FOURIER TRANSFORM

DFT = $\sum_{n=1}^N [x][e] \rightarrow O(n^2)$

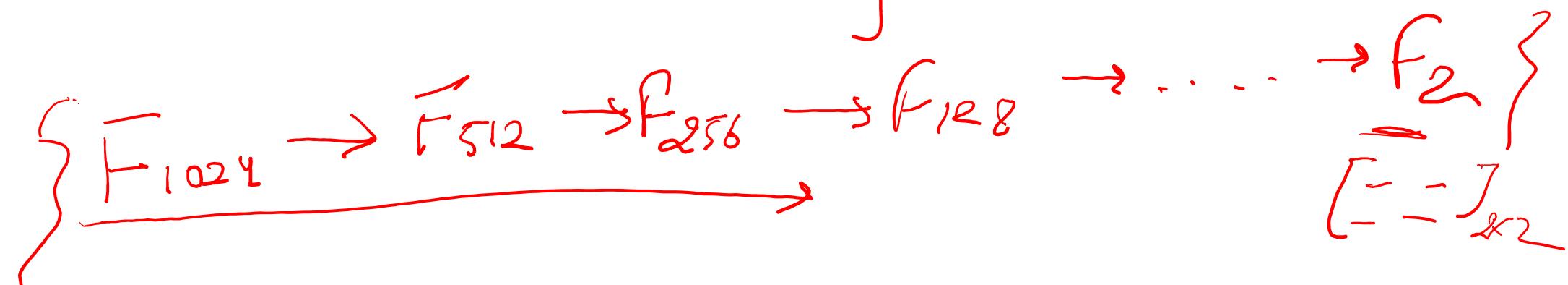
FFT $\rightarrow O(n \log n)$

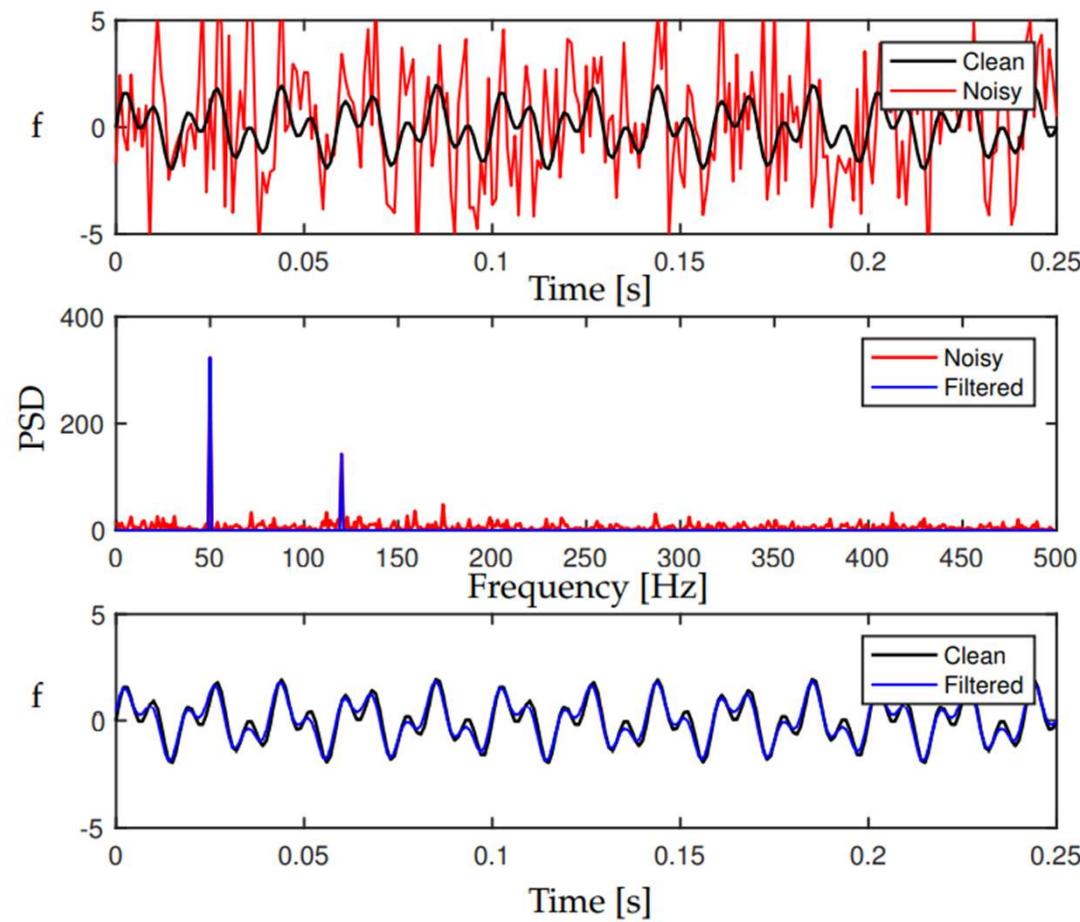


$$\hat{f} = \overline{\hat{F}_{1024}} f \quad \left\{ n = 1024 \text{ or } \underline{2^{10}} \right\}$$

$$= \frac{\begin{bmatrix} I_{512} & -D_{512} \\ I_{512} & -D_{512} \end{bmatrix} \begin{bmatrix} \hat{F}_{512} & 0 \\ 0 & \hat{F}_{512} \end{bmatrix} \begin{bmatrix} \text{for even} \\ \text{for odd} \end{bmatrix}}{\dots} \quad \left\{ \begin{array}{l} t_1 \\ f_1 \\ t_3 \\ f_3 \\ \vdots \\ t_m \\ f_m \end{array} \right\}$$

$$\underline{D_{512}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \omega & 0 & 0 \\ 0 & 0 & \omega^2 & 0 \\ 0 & 0 & 0 & \omega^{512} \end{bmatrix}$$





Wavelet Transform

- FFT \rightarrow basis $f^n \rightarrow$ cosine & sine
 - Signals which are non-periodic, finite, discontinuous
EEG \rightarrow non-stationary
- ① \rightarrow Perform Fourier analysis over short time windows
known as Short time Fourier transform (\rightarrow STFTs)



Wavelet transform

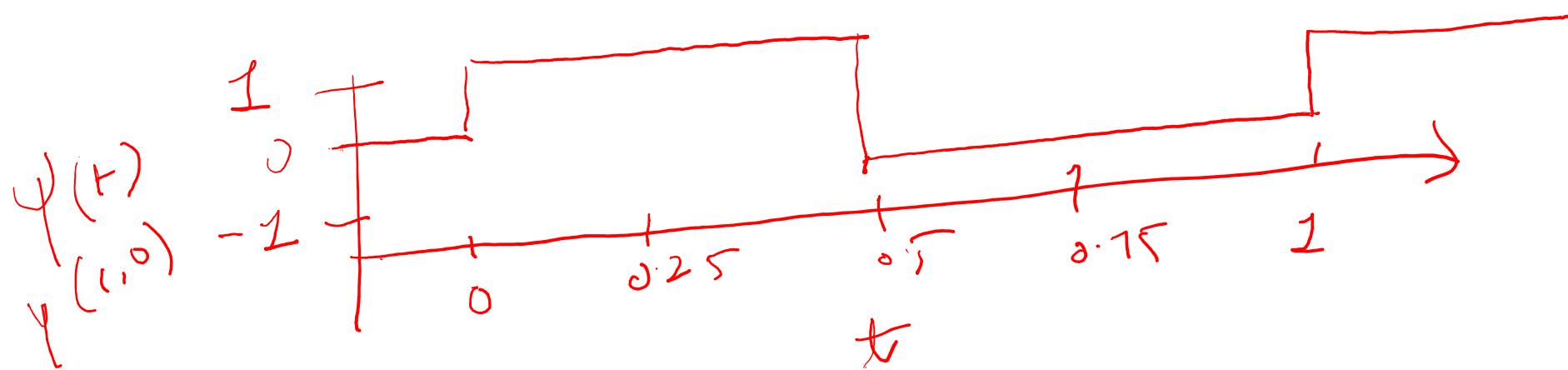
finite Basis function \rightarrow wavelets \rightarrow scaled over a
single finite length waveform \rightarrow Mother Wavelets

$\psi(t) \rightarrow$ mother wavelet

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)$$

Haar wavelet

$$\psi(t) = \begin{cases} 1 & 0 \leq t < \frac{1}{2} \\ -1 & -\frac{1}{2} \leq t \leq 1 \\ 0 & \text{otherwise} \end{cases}$$



continuous WT

$$\underline{\mathcal{W}_\psi(f)(a,b)} = \langle f, \Psi_{a,b} \rangle = \int_{-\infty}^{\infty} f(t) \underline{\Psi_{a,b}(t)} dt$$

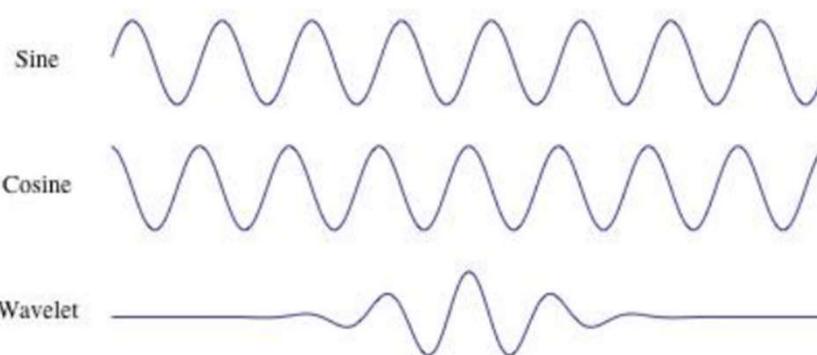
Inverse CWT

$$f(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \mathcal{W}_\psi(f)(a,b) \underline{\Psi_{a,b}(t)} \frac{da db}{a^2}$$

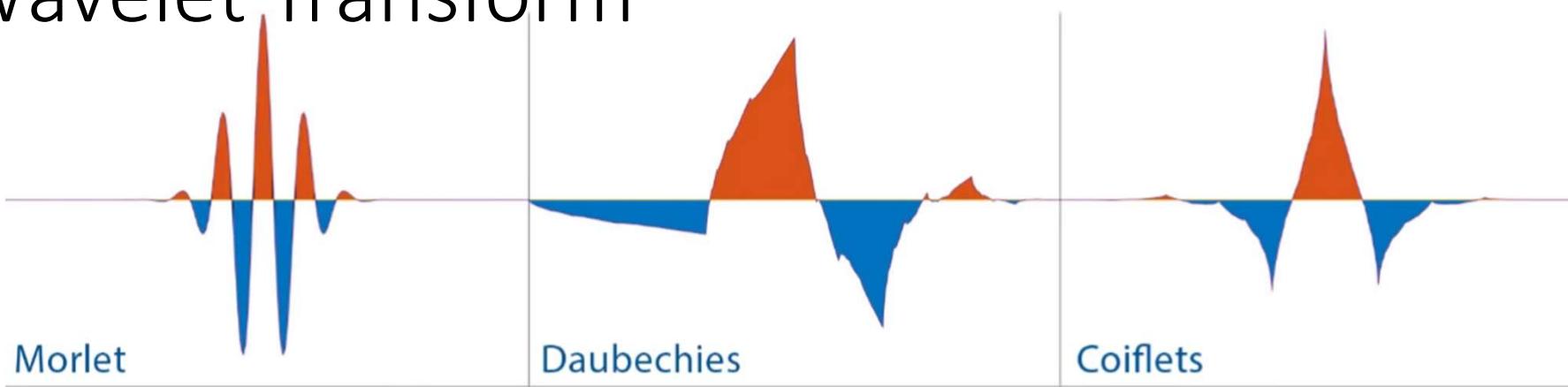
$$C_\psi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega$$

$$\underbrace{\mathcal{D}\omega^T}_{\mathcal{D}\psi(f)}(j,k) = \langle f, \psi_{j,k} \rangle = \int_{-\infty}^{\infty} f(t) \psi_{j,k}(t) dt$$

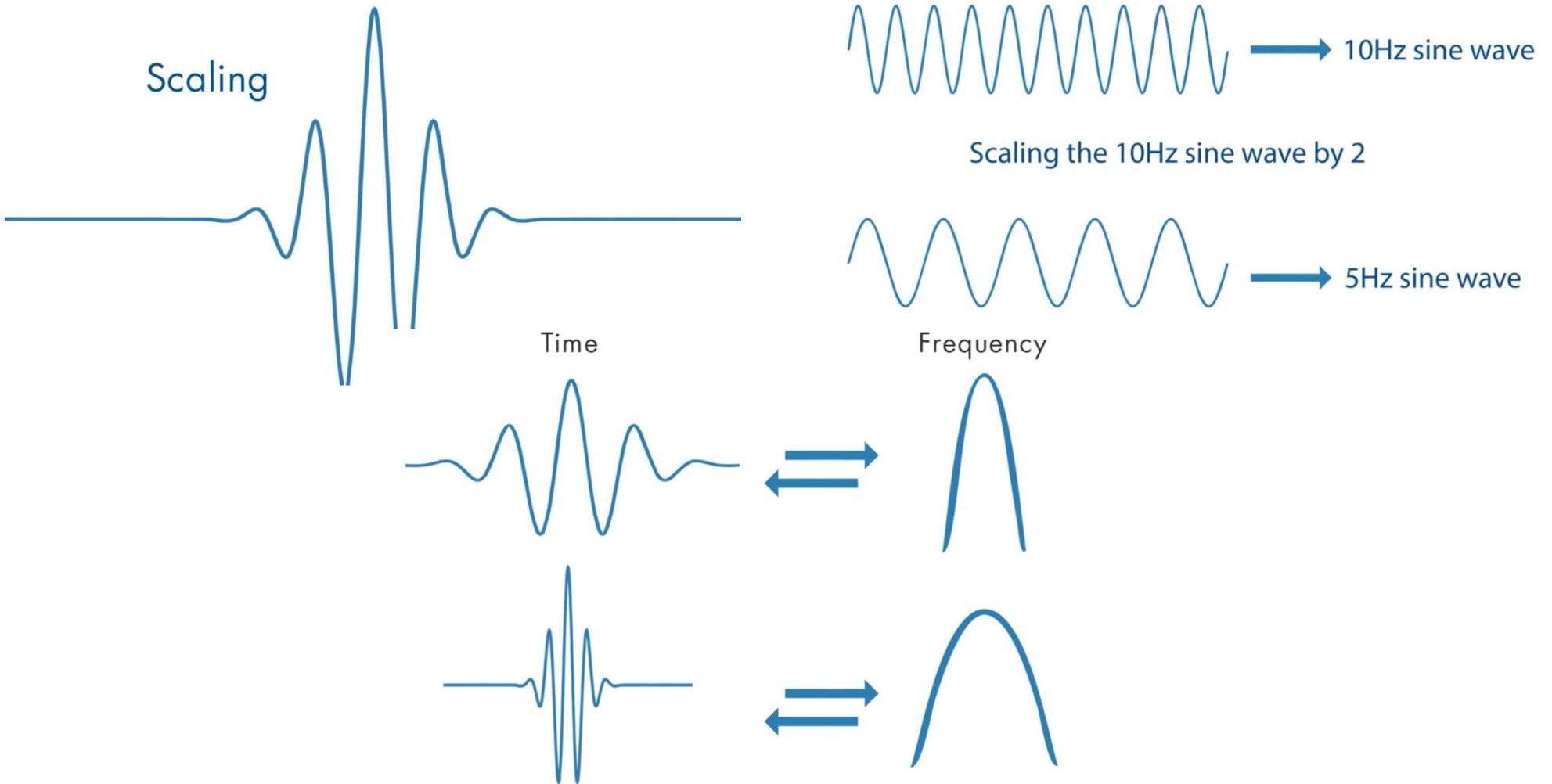
$$\psi_{j,k}(t) = \frac{1}{a_j^0} \psi\left(\frac{\theta - k\beta}{a_j^0}\right)$$



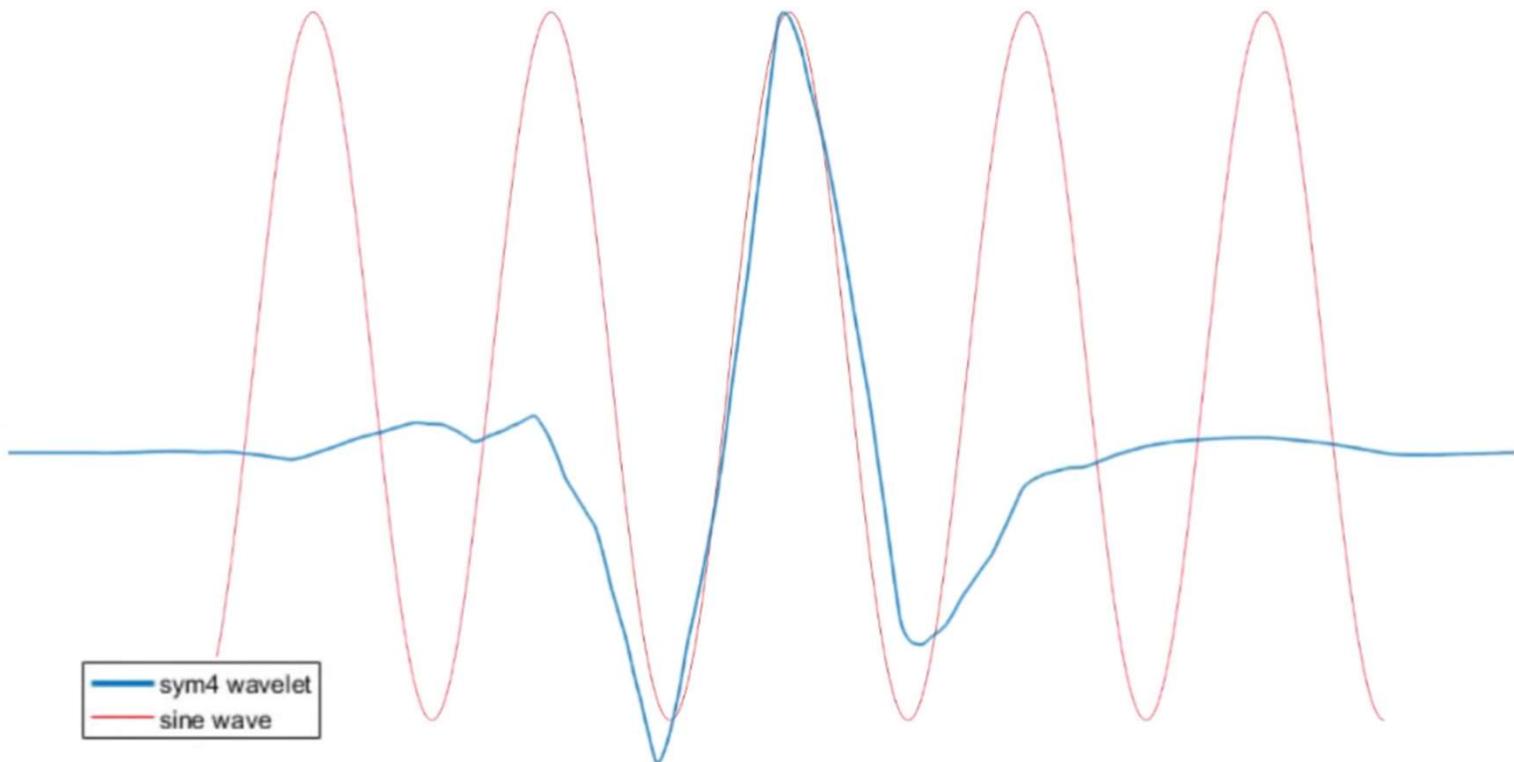
Wavelet Transform



Wavelet Transform

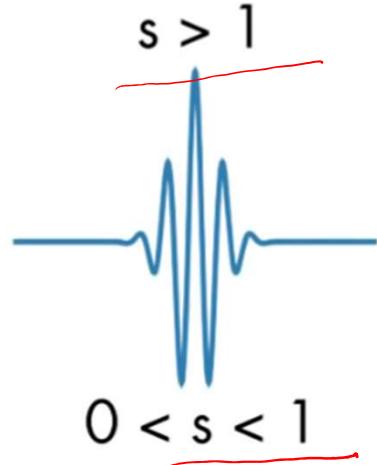


Wavelet Transform



Comparison of a Wavelet with a Sine Wave of Same Frequency

Wavelet Transform



$$\Psi\left(\frac{t}{s}\right)$$



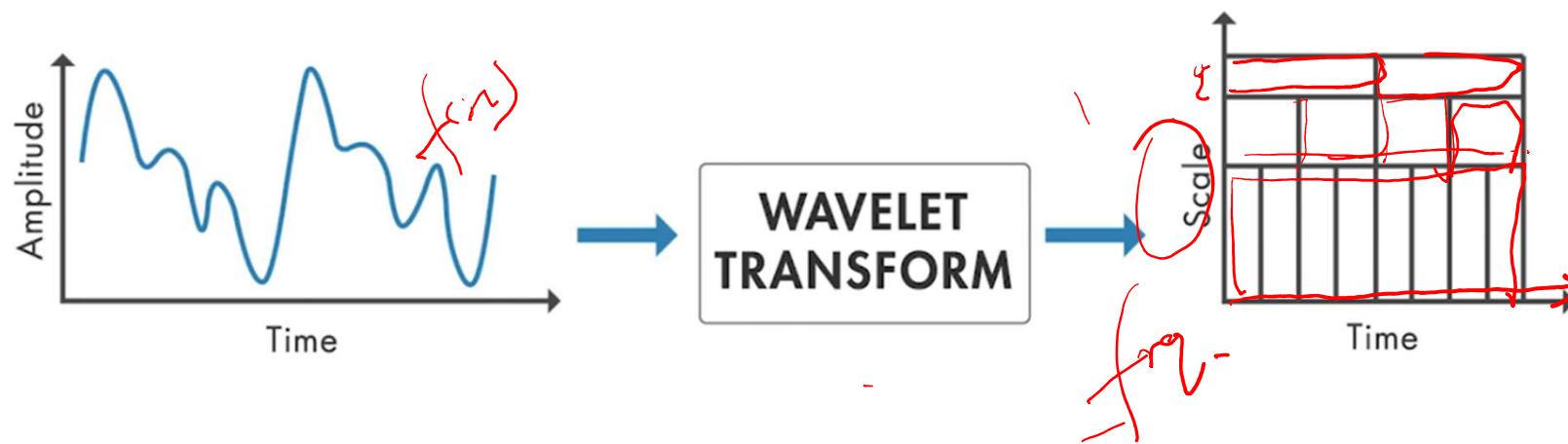
large scale factor
low frequency



small scale factor
high frequency

$\Psi(t)$ $\frac{1}{\sqrt{a}}$

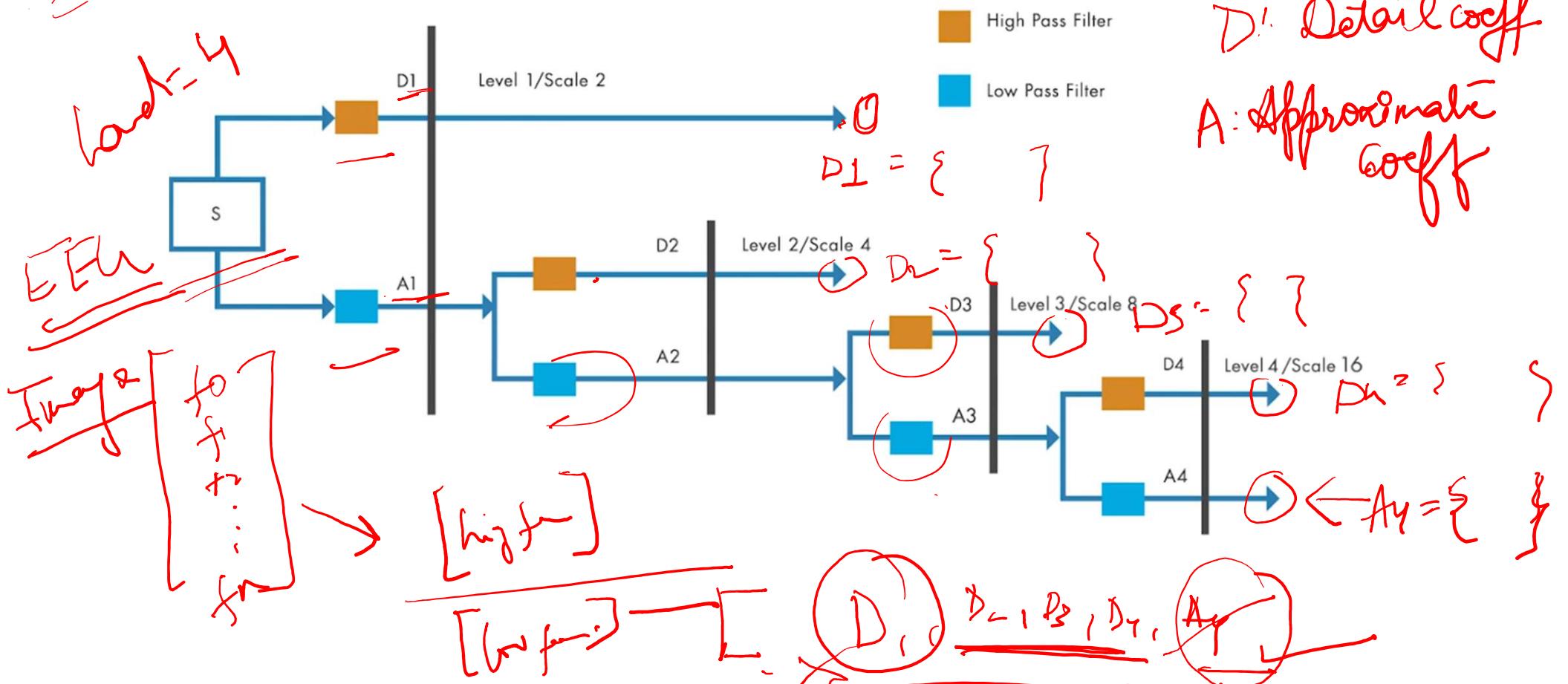
Continuous Wavelet Transform

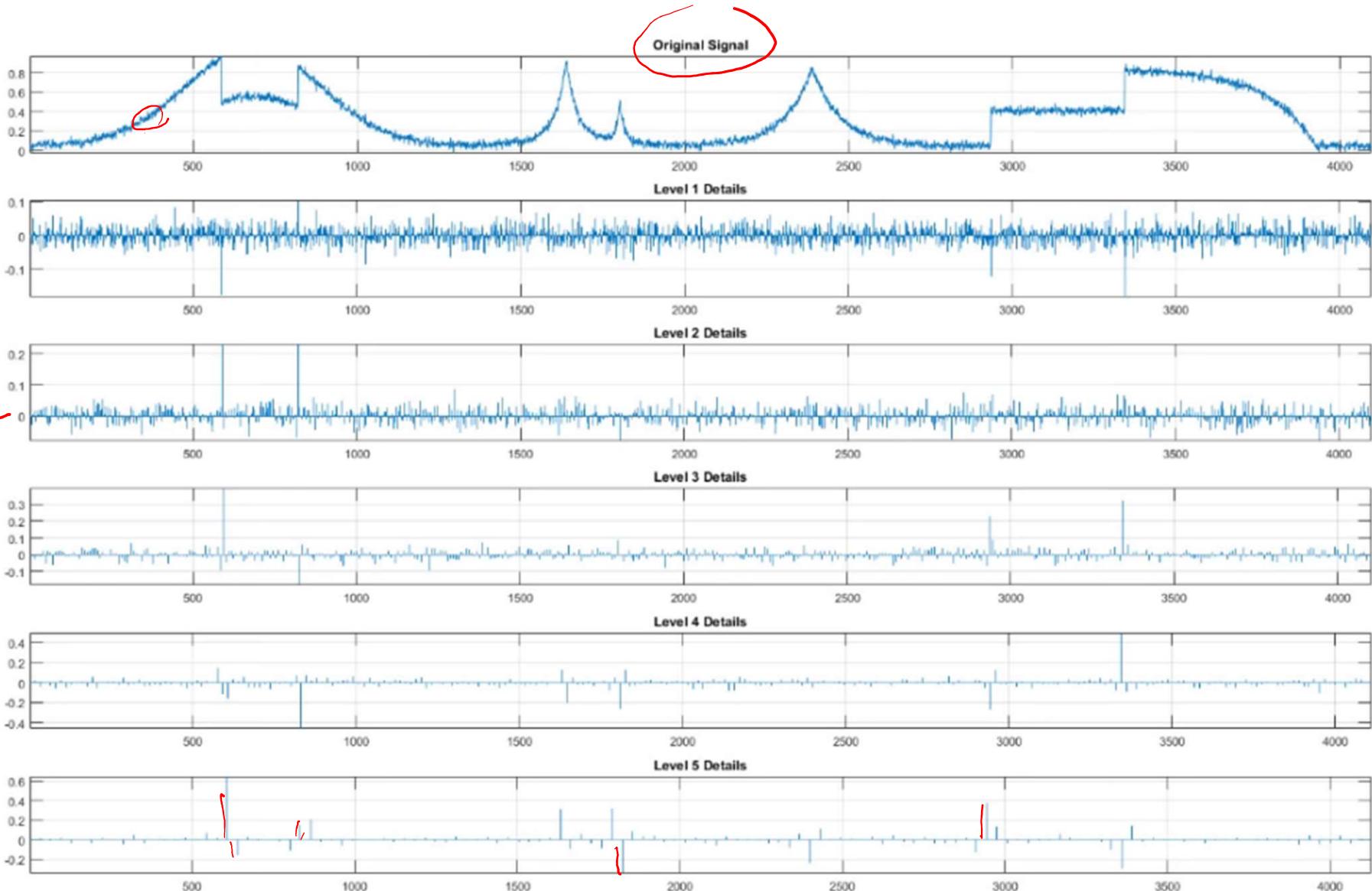


Discrete Wavelet Transform

← EEG

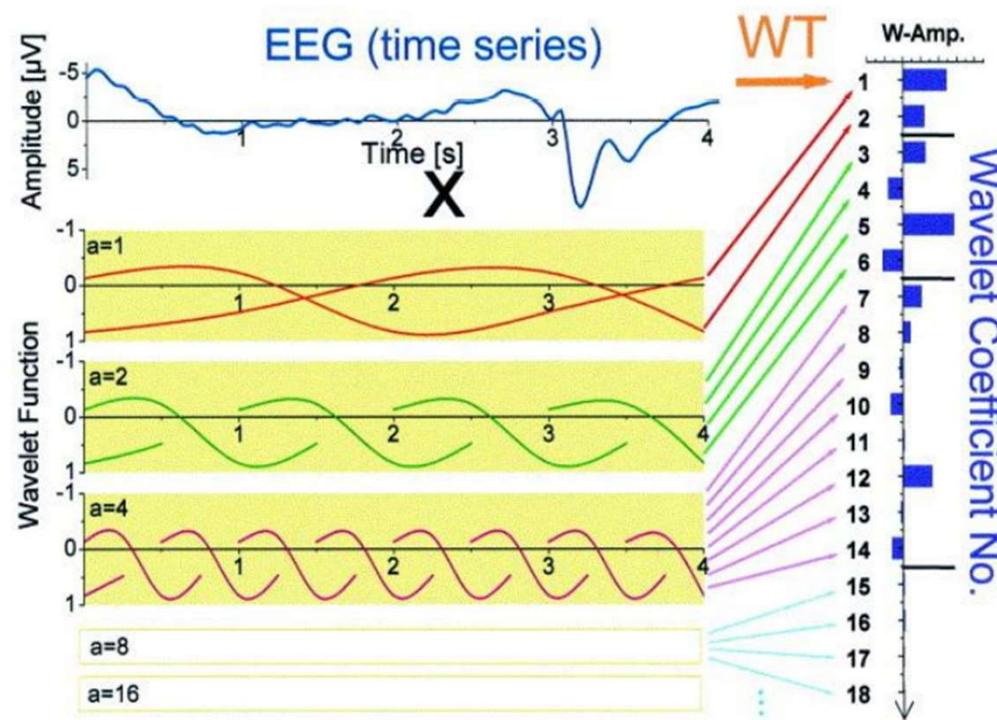
FFT/DWT





DWT
Levels

Example: Wavelet Decomposition of EEG



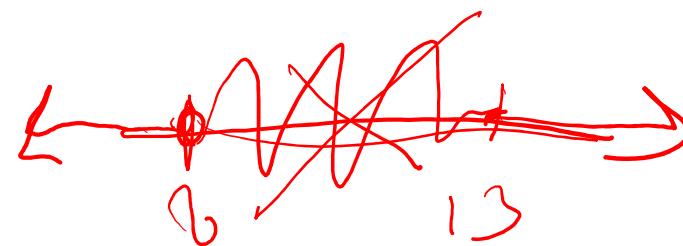
Credits: (Hinterberger et al., 2003) ↗

Filters

- High Pass Filter:
 - Blocks dc offset in high gain amplifiers or single supply circuits. Filters can be used to separate signals, passing those of interest, and attenuating the unwanted frequencies.
- Low Pass Filter:
 - Stabilizes amplifiers by rolling off the gain at higher frequencies where excessive phase shift may cause oscillations

Filters

- Band Pass Filter:
 - If a high-pass filter and a low-pass filter are cascaded, a band pass filter is created. The band pass filter passes a band of frequencies between a lower cutoff frequency, f_L , and an upper cutoff frequency, f_h
- Notch (Band Reject Filter):
 - The pass bands include frequencies below f_L and above f_h . The band from f_L to f_h is in the stop band.



TIME DOMAIN ANALYSIS

① Hjorth Parameters [1970s] ← EEG $s(t)$

↳ Mean Power

↳ RMS freq.

↳ RMS freq. spread

② Activity

$$A = a_0$$

a_0 : variance of signal in
the epoch under measure
-ment

③ Mobility

$$M = \sqrt{\frac{a_2}{a_0}}$$

$$a_2 = \text{variance of } \frac{ds(t)}{dt}$$

④ Complexity

$$C = \sqrt{\frac{a_4}{a_0}}$$

$$a_4: \text{variance of } \frac{d^2 s(t)}{dt^2}$$

② AutoRegressive Modeling (AR)

$$x_t = \sum_{i=1}^p a_i x_{t-i} + \epsilon_t$$

ϵ_t - some white noise

p - order of AR model

Adaptive AutoRegressive-(AAR) Model.

$$x_t = \sum_{i=1}^p \underbrace{a_{i,t}}_{\uparrow \text{Statistical structure over time}} x_{t-i} + \epsilon_t$$

Spatial Filtering

Spatial Filtering

- Spatial filtering techniques take as input brain signals recorded from several different locations (or “channels”) and transform them in one of several ways.
- Possible goals include
 - enhancing local activity
 - reducing noise that is common across channels,
 - decreasing the dimensionality of the data,
 - finding projections that maximize discrimination between different classes

Bipolar

- Extract bipolar signals

$$\widetilde{S_{i,j}} = S_i - S_j$$

- Highlight the **electrical potential differences** between the two electrodes of interest (i and j).

Laplacian

- *Laplacian filtering*, extracts local activity at electrode i by subtracting the average activity present in the four orthogonal nearest neighboring electrodes

$$\tilde{s} = s_i - \frac{1}{4} \sum_{i \in \theta} s_i$$

Common Average Referencing

- *Common average referencing* (CAR), enhances the local activity at electrode i by subtracting the average over all electrodes

$$\tilde{s}_i = s_i - \frac{1}{N} \sum_{i=1}^N s_i$$

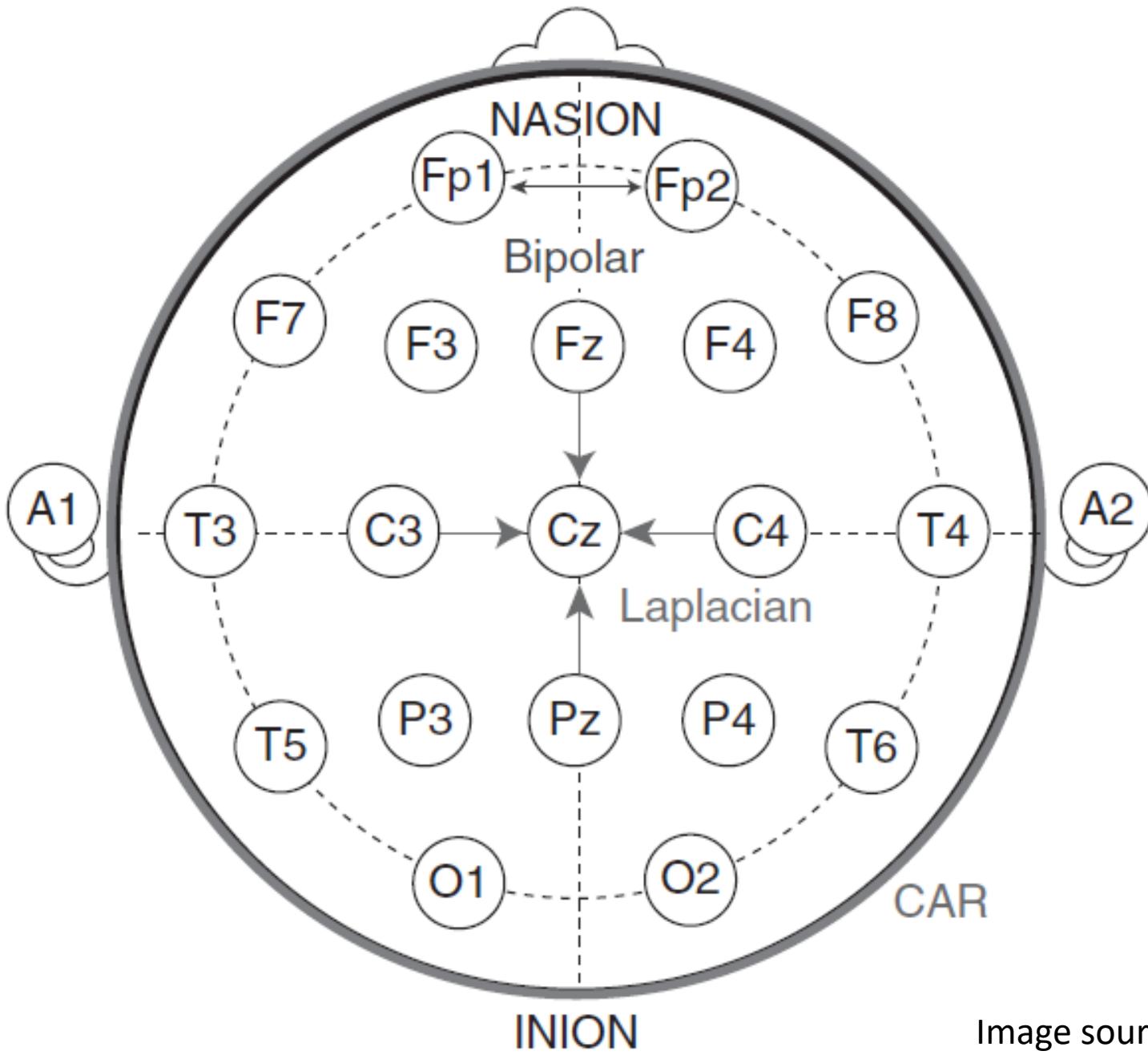


Image source: Rajesh P.N, Rao- Brain Computer Interfacing: An Introduction

Vector Representation

- A vector $\mathbf{x} \in \mathbb{R}^n$ can be represented by **n** components:
- Assuming the standard base $\langle \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_N \rangle$ (i.e., unit vectors in each dimension), x_i can be obtained by **projecting** \mathbf{x} along the direction of \mathbf{v}_i :
- \mathbf{x} can be “**reconstructed**” from its projections as follows:
- Since the basis vectors are the same for all $\mathbf{x} \in \mathbb{R}^n$ (standard basis), we typically represent them as a **n**-component vector.

$$\mathbf{x} : \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_N \end{bmatrix}$$

$$x_i = \frac{\mathbf{x}^T \mathbf{v}_i}{\mathbf{v}_i^T \mathbf{v}_i} = \mathbf{x}^T \mathbf{v}_i$$

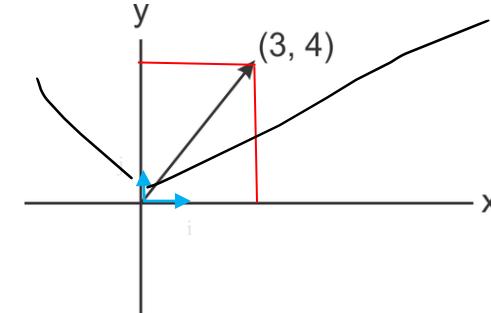
$$\mathbf{x} = \sum_{i=1}^N x_i \mathbf{v}_i = x_1 \mathbf{v}_1 + x_2 \mathbf{v}_2 + \dots + x_N \mathbf{v}_N$$



Vector Representation (cont'd)

- Example assuming $n=2$:

$$\mathbf{x} : \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 3 \\ 4 \end{bmatrix}$$



- Assuming the standard base $\langle v_1=i, v_2=j \rangle$, x_i can be obtained by projecting x along the direction of v_i :

$$x_1 = \mathbf{x}^T i = [3 \quad 4] \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 3$$

$$x_2 = \mathbf{x}^T j = [3 \quad 4] \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 4$$

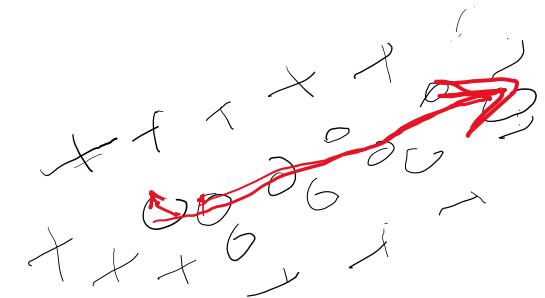
- \mathbf{x} can be “reconstructed” from its projections as follows:

$$\mathbf{x} = 3i + 4j$$

Principal Component Analysis

- The goal in *principal component analysis* (PCA) (also called the *Karhunen-Loeve* or *Hotelling transform*) is to discover the underlying statistical variability in the data and reduce the data's dimensionality from D to a much smaller number of dimensions L ($L \ll D$).
- PCA achieves this goal by
 - Finding the directions of maximum variance in the D -dimensional data
 - Rotating the original coordinate system to align with these directions of maximum variance

Principal Component Analysis



- Most natural signals, including brain signals are redundant
- In the case of EEG measurements from N electrodes
 - Measurements from nearby electrodes may be correlated
 - Underlying rhythms across multiple electrodes.
- PCA attempts to find the dominant directions of variability in the data.
- New data points can be projected along the “principal” directions. Each projection is called a “principal component”
- The resulting L -dimensional vector can be used as a feature vector for classification or other purposes in BCI applications

Principal Component Analysis (PCA)

- If $\mathbf{x} \in \mathbb{R}^N$, then it can be written as a linear combination of an **orthonormal** set of N basis vectors $\langle \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_N \rangle$ in \mathbb{R}^N (e.g., using the standard base):

$$\mathbf{v}_i^T \mathbf{v}_j = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbf{x} = \sum_{i=1}^N x_i \mathbf{v}_i = x_1 \mathbf{v}_1 + x_2 \mathbf{v}_2 + \dots + x_N \mathbf{v}_N$$

where $x_i = \frac{\mathbf{x}^T \mathbf{v}_i}{\mathbf{v}_i^T \mathbf{v}_i} = \mathbf{x}^T \mathbf{v}_i$

$$\mathbf{x} : \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$



- PCA seeks to **approximate** \mathbf{x} in a **subspace** of \mathbb{R}^N using a **new** set of $K < N$ basis vectors $\langle \mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_K \rangle$ in \mathbb{R}^N :

$$\hat{\mathbf{x}} = \sum_{i=1}^K y_i \mathbf{u}_i = y_1 \mathbf{u}_1 + y_2 \mathbf{u}_2 + \dots + y_K \mathbf{u}_K$$

(reconstruction)

such that $\|\mathbf{x} - \hat{\mathbf{x}}\|$ is **minimized!**
(i.e., minimize information loss)

$$\hat{\mathbf{x}} : \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_K \end{bmatrix}$$

Principal Component Analysis (PCA)

- The “**optimal**” set of basis vectors $\langle u_1, u_2, \dots, u_K \rangle$ can be found as follows (we will see why):

(1) Find the **eigenvectors** u_i of the **covariance** matrix of the (training) data Σ_x

$$\Sigma_x u_i = \lambda_i u_i$$

(2) Choose the K “**largest**” eigenvectors u_i (i.e., corresponding to the K “**largest**” eigenvalues λ_i)

$\langle u_1, u_2, \dots, u_K \rangle$ correspond to the “optimal” basis!

We refer to the “**largest**” eigenvectors u_i as **principal components**.

PCA - Steps

- Suppose we are given $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_M$ ($N \times 1$) vectors

N: # of features

Step 1: compute sample mean

M: # data

$$\bar{\mathbf{x}} = \frac{1}{M} \sum_{i=1}^M \mathbf{x}_i$$

Step 2: subtract sample mean (i.e., center data at zero)

$$\Phi_i = \mathbf{x}_i - \bar{\mathbf{x}}$$

Step 3: compute the sample covariance matrix Σ_x

$$\Sigma_x = \frac{1}{M} \sum_{i=1}^M (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T = \frac{1}{M} \sum_{i=1}^M \Phi_i \Phi_i^T = \frac{1}{M} A A^T$$

where $A = [\Phi_1 \ \Phi_2 \ \dots \ \Phi_M]$
i.e., the columns of A are the Φ_i
($N \times M$ matrix)

PCA - Steps

Step 4: compute the eigenvalues/eigenvectors of Σ_x

$$\Sigma_x u_i = \lambda_i u_i$$

where we assume $\lambda_1 > \lambda_2 > \dots > \lambda_N$

Note : most software packages return the eigenvalues (and corresponding eigenvectors) in **decreasing** order – if not, you can explicitly put them in this order)

Since Σ_x is symmetric, $\langle u_1, u_2, \dots, u_N \rangle$ form an **orthogonal** basis in R^N and we can represent **any** $x \in R^N$ as:

$$x - \bar{x} = \sum_{i=1}^N y_i u_i = y_1 u_1 + y_2 u_2 + \dots + y_N u_N$$

$$y_i = \frac{(x - \bar{x})^T u_i}{u_i^T u_i} = (x - \bar{x})^T u_i \quad \text{if } \|u_i\| = 1$$

i.e., this is
just a “**change**”
of basis!

$$\begin{matrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x_N \end{matrix} \rightarrow \begin{matrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ y_N \end{matrix}$$

Note : most software packages **normalize** u_i to unit length to simplify calculations; if not, you can explicitly normalize them)

PCA - Steps

Step 5: dimensionality reduction step – approximate \mathbf{x} using only the **first** K eigenvectors ($K \ll N$) (i.e., corresponding to the **K largest** eigenvalues where K is a **parameter**):

$$\mathbf{x} - \bar{\mathbf{x}} = \sum_{i=1}^N y_i \mathbf{u}_i = y_1 \mathbf{u}_1 + y_2 \mathbf{u}_2 + \dots + y_N \mathbf{u}_N \quad \begin{matrix} \nearrow \\ N \end{matrix} \quad \begin{matrix} \searrow \\ K \end{matrix}$$

approximate \mathbf{x} by $\hat{\mathbf{x}}$
using first K eigenvectors only

$$\hat{\mathbf{x}} - \bar{\mathbf{x}} = \sum_{i=1}^K y_i \mathbf{u}_i = y_1 \mathbf{u}_1 + y_2 \mathbf{u}_2 + \dots + y_K \mathbf{u}_K$$

(reconstruction)

$$\mathbf{x} - \bar{\mathbf{x}}: \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_N \end{bmatrix} \rightarrow \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_N \end{bmatrix} \rightarrow \hat{\mathbf{x}} - \bar{\mathbf{x}}: \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_K \end{bmatrix}$$

note that if $\underbrace{K=N}$, then $\hat{\mathbf{x}} = \mathbf{x}$
(i.e., zero reconstruction error)

What is the Linear Transformation implied by PCA?

- The linear transformation $y = Tx$ which performs the dimensionality reduction in PCA is:

$$\hat{\mathbf{x}} - \bar{\mathbf{x}} = \sum_{i=1}^K y_i u_i = y_1 u_1 + y_2 u_2 + \dots + y_K u_K$$

$$(\hat{\mathbf{x}} - \bar{\mathbf{x}}) = U \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_K \end{bmatrix}$$

where $U = [u_1 \ u_2 \ \dots \ u_K]$ $N \times K$ matrix
i.e., the columns of U are the the first K eigenvectors of Σ_x


$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ \vdots \\ y_K \end{bmatrix} = U^T (\hat{\mathbf{x}} - \bar{\mathbf{x}})$$

$T = U^T$ $K \times N$ matrix
i.e., the rows of T are the first K eigenvectors of Σ_x

What is the form of Σ_y ?

$$\Sigma_x = \frac{1}{M} \sum_{i=1}^M (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T = \frac{1}{M} \sum_{i=1}^M \Phi_i \Phi_i^T$$

Using diagonalization:

$$\Sigma_x = P \Lambda P^T$$

The columns of P are the
eigenvectors of Σ_x

The diagonal elements of
 Λ are the **eigenvalues** of Σ_x
or the **variances**

$$\mathbf{y}_i = U^T (\mathbf{x}_i - \bar{\mathbf{x}}) = P^T \Phi_i$$

$$\Sigma_y = \frac{1}{M} \sum_{i=1}^M (\mathbf{y}_i - \bar{\mathbf{y}})(\mathbf{y}_i - \bar{\mathbf{y}})^T = \frac{1}{M} \sum_{i=1}^M (\mathbf{y}_i)(\mathbf{y}_i)^T = \frac{1}{M} \sum_{i=1}^M (P^T \Phi_i)(P^T \Phi_i)^T =$$

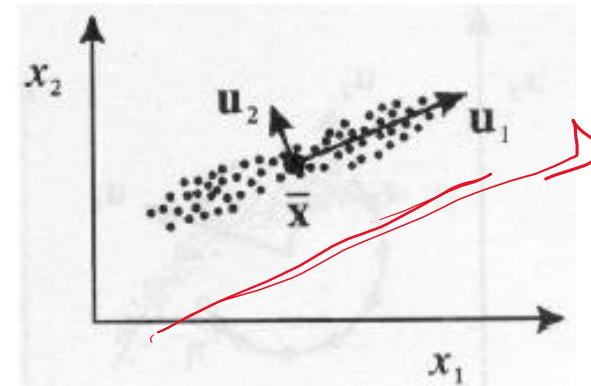
$$\frac{1}{M} \sum_{i=1}^M (P^T \Phi_i)(\Phi_i^T P) = P^T \left(\frac{1}{M} \sum_{i=1}^M \Phi_i \Phi_i^T \right) P = P^T \Sigma_x P = P^T (P \Lambda P^T) P = \Lambda$$

$$\Sigma_y = \Lambda$$

PCA de-correlates the data!
Preserves original variances!

Interpretation of PCA

- PCA chooses the **eigenvectors** of the covariance matrix corresponding to the **largest** eigenvalues.
- The **eigenvalues** correspond to the **variance** of the data along the eigenvector directions.
- Therefore, PCA projects the data along the directions where the data varies **most**.
- PCA preserves as much **information** in the data by preserving as much **variance** in the data.



u_1 : direction of **max** variance
 u_2 : orthogonal to u_1

Example

- Compute the PCA of the following dataset:

(1,2),(3,3),(3,5),(5,4),(5,6),(6,5),(8,7),(9,8)

- Compute the sample covariance matrix is:

$$\hat{\Sigma} = \frac{1}{n} \sum_{k=1}^n (\mathbf{x}_k - \hat{\mu})(\mathbf{x}_k - \hat{\mu})^t$$

$$\Sigma_x = \begin{bmatrix} 6.25 & 4.25 \\ 4.25 & 3.5 \end{bmatrix}$$

- The eigenvalues can be computed by finding the roots of the characteristic polynomial:

$$\begin{aligned}\Sigma_x v &= \lambda v \Rightarrow |\Sigma_x - \lambda I| = 0 \\ &\Rightarrow \begin{vmatrix} 6.25 - \lambda & 4.25 \\ 4.25 & 3.5 - \lambda \end{vmatrix} = 0 \\ &\Rightarrow \lambda_1 = 9.34; \lambda_2 = 0.41\end{aligned}$$

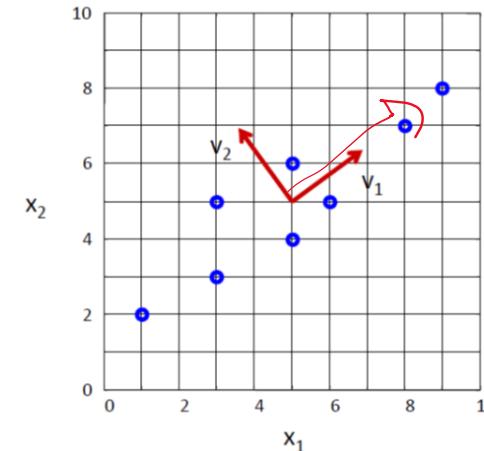
Example (cont'd)

- The eigenvectors are the solutions of the systems:

$$\sum_{\mathbf{x}} \mathbf{u}_i = \lambda_i \mathbf{u}_i$$



$$\begin{bmatrix} 6.25 & 4.25 \\ 4.25 & 3.5 \end{bmatrix} \begin{bmatrix} v_{11} \\ v_{12} \end{bmatrix} = \begin{bmatrix} \lambda_1 v_{11} \\ \lambda_1 v_{12} \end{bmatrix} \Rightarrow \begin{bmatrix} v_{11} \\ v_{12} \end{bmatrix} = \begin{bmatrix} 0.81 \\ 0.59 \end{bmatrix}$$
$$\begin{bmatrix} 6.25 & 4.25 \\ 4.25 & 3.5 \end{bmatrix} \begin{bmatrix} v_{21} \\ v_{22} \end{bmatrix} = \begin{bmatrix} \lambda_2 v_{21} \\ \lambda_2 v_{22} \end{bmatrix} \Rightarrow \begin{bmatrix} v_{21} \\ v_{22} \end{bmatrix} = \begin{bmatrix} -0.59 \\ 0.81 \end{bmatrix}$$



Note: if \mathbf{u}_i is a solution, then $c\mathbf{u}_i$ is also a solution where $c \neq 0$.

Eigenvectors can be normalized to unit-length using:

$$\hat{\mathbf{v}}_i = \frac{\mathbf{v}_i}{\| \mathbf{v}_i \|}$$

How do we choose K ?

- K is typically chosen based on how much **information (variance)** we want to preserve:

Choose the **smallest**
 K that satisfies
the following
inequality:

$$\frac{\sum_{i=1}^K \lambda_i}{\sum_{i=1}^N \lambda_i} > T \quad \text{where } T \text{ is a threshold (e.g., 0.9)}$$

- If $T=0.9$, for example, we “**preserve**” 90% of the information (variance) in the data.
- If $K=N$, then we “**preserve**” 100% of the information in the data (i.e., just a “**change**” of basis and $\hat{\mathbf{x}} = \mathbf{x}$)

Approximation Error

- The approximation error (or reconstruction error) can be computed by:

$$\| \mathbf{x} - \hat{\mathbf{x}} \|$$

where $\hat{\mathbf{x}} = \sum_{i=1}^K y_i \mathbf{u}_i + \bar{\mathbf{x}} = y_1 \mathbf{u}_1 + y_2 \mathbf{u}_2 + \dots + y_K \mathbf{u}_K + \bar{\mathbf{x}}$
(reconstruction)

- It can also be shown that the approximation error can be computed as follows:

$$\| \mathbf{x} - \hat{\mathbf{x}} \| = \frac{1}{2} \sum_{i=K+1}^N \lambda_i$$

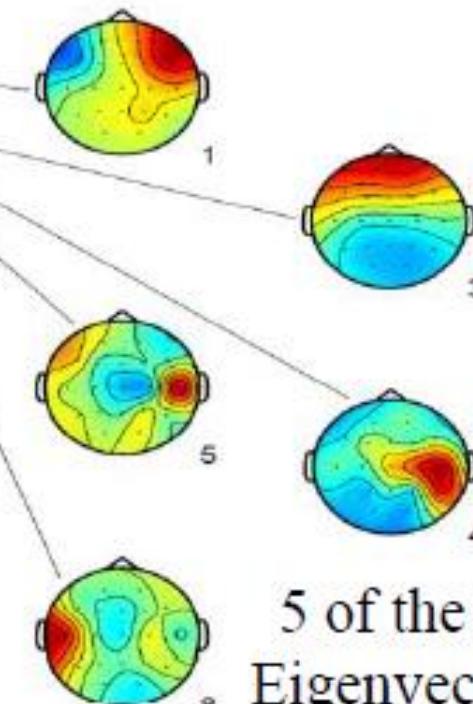
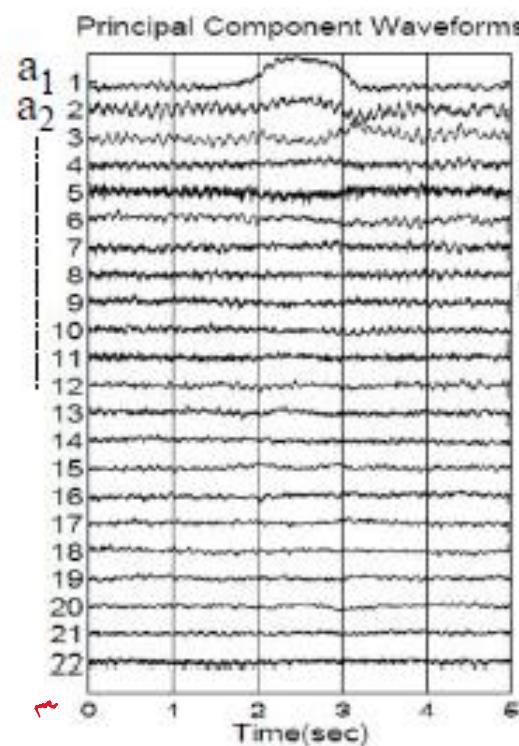
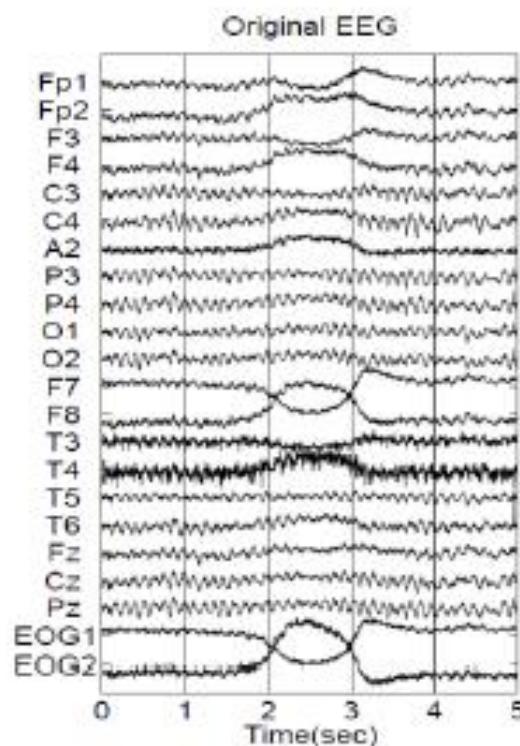


Data Normalization

- The principal components are dependent on the *units* used to measure the original variables as well as on the *range* of values they assume.
- Data should **always** be normalized prior to using PCA.
- A common normalization method is to transform all the data to have **zero mean** and **unit standard deviation**:

$$\frac{x_i - \mu}{\sigma} \quad \text{where } \mu \text{ and } \sigma \text{ are the mean and standard deviation of the } i\text{-th feature } x_i$$

PCA applied to EEG



5 of the 22
Eigenvectors
(spatial filters
for EEG
channels)

(Jung et al., 1998)

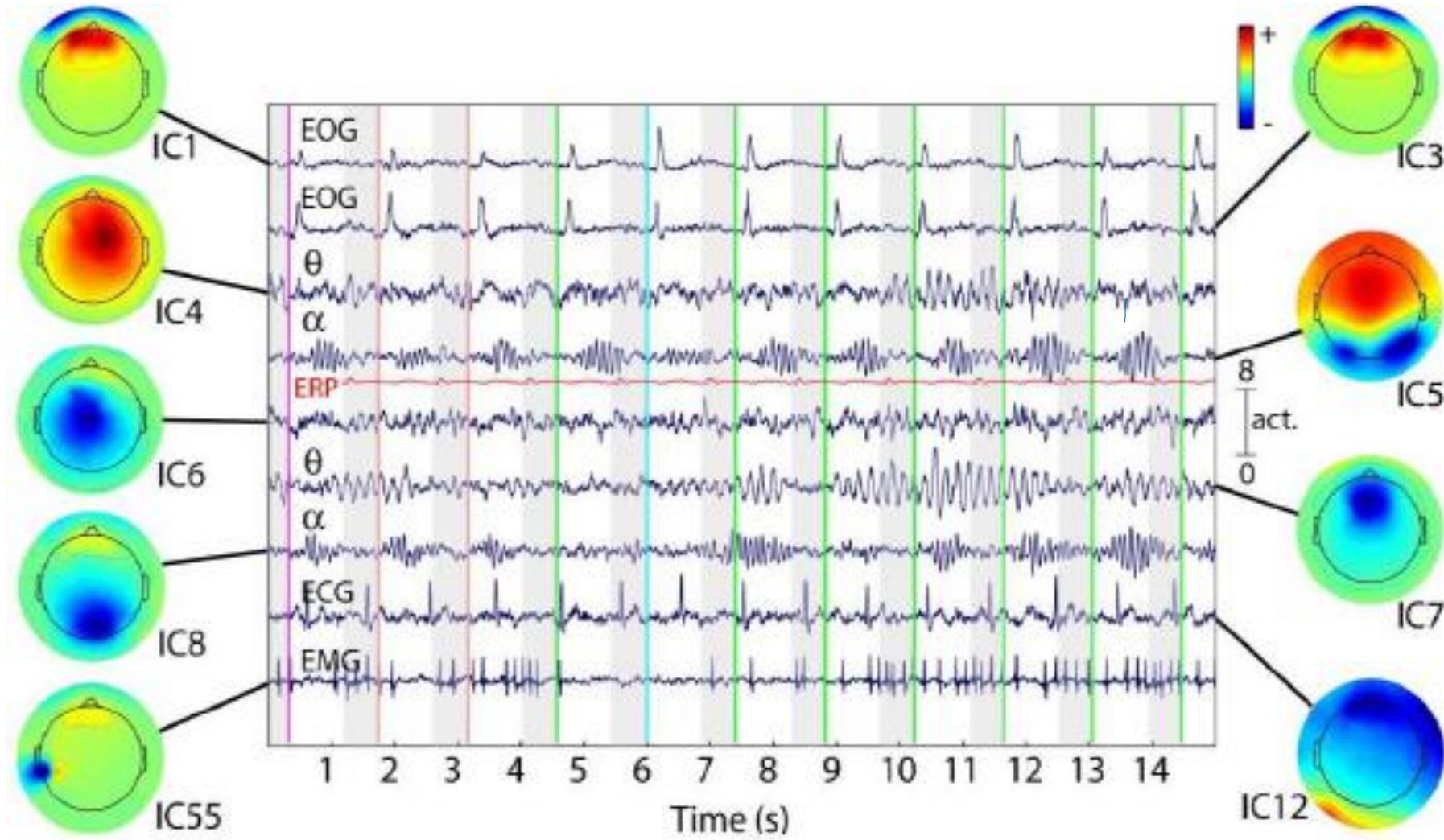
Independent Component Analysis

- PCA finds a matrix \mathbf{V} that decorrelates the inputs but the resulting feature vector \mathbf{a} may still retain higher order statistical dependencies
- There may be a possibility that the variables are independent.
- ICA tries to find a matrix \mathbf{W} of filters (columns of \mathbf{W}) such that the output \mathbf{a} is **statistically independent**:

$$\mathbf{a} = \mathbf{W}^T \mathbf{x} \text{ such that } P(\mathbf{a}) \approx \prod_{i=1}^D P(a_i)$$

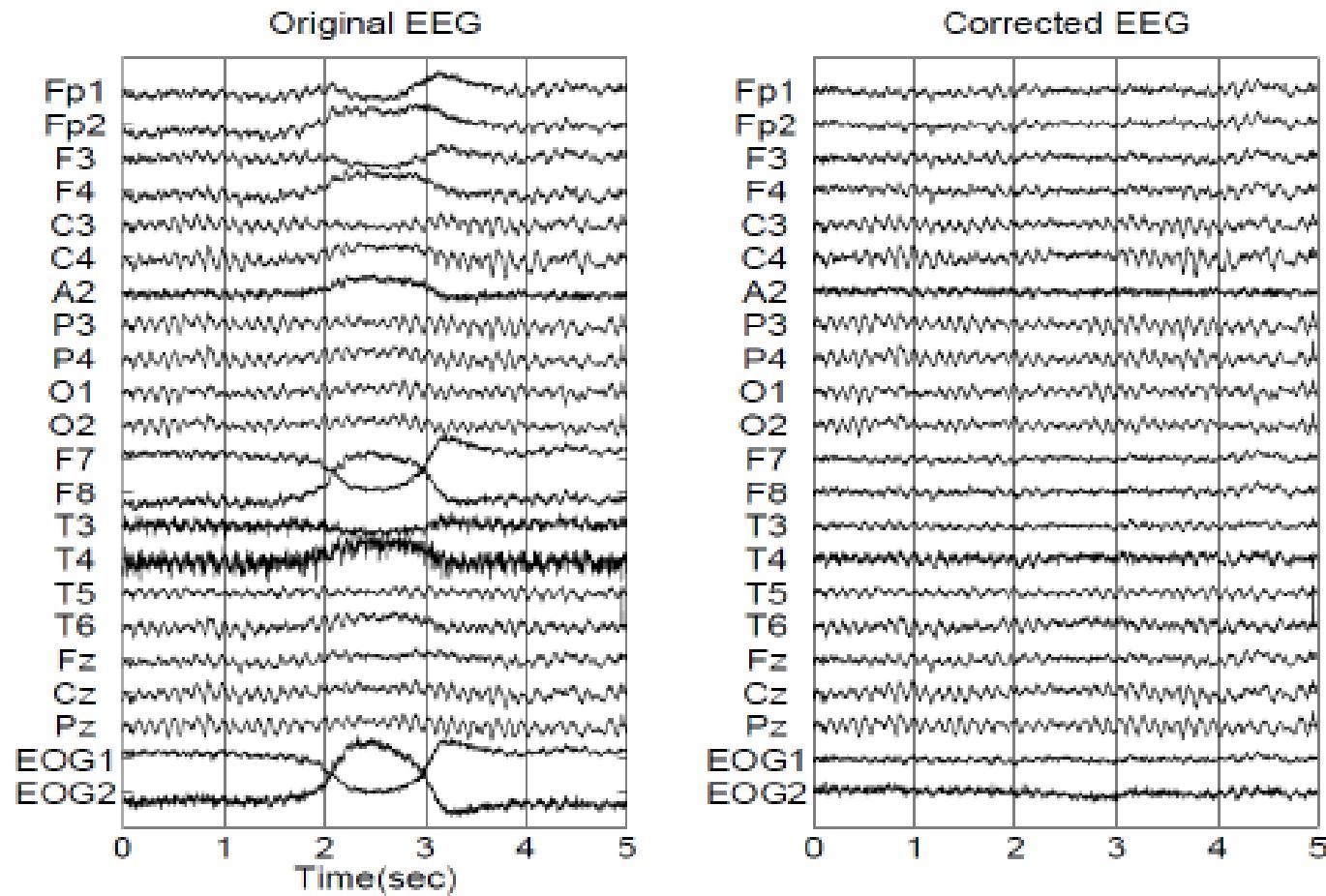
Independent Component Analysis

- ICA assumes sources are linearly mixed to produce x
- The feature vector dimension in ICA can be lesser than, equal to, or greater than the number of input dimensions.
- ICA has proved useful in a variety of settings in BCI applications, ranging from the use of the output vector **a** as a feature vector in classification.



Application of ICA to EEG data for isolating electro- oculographic (EOG) (eye-related), electromyographic (EMG) (muscle-related) and electrocardiographic (ECG) (heart-related) artifacts, and unmixing putative source signals in the brain. Image (adapted from Onton and Makeig, 2006)

ICA for Artifact Removal in EEG



Common Spatial Pattern

- Supervised Technique
- Data is labeled with class to which each data vector belongs
 - E.g., EEG obtained for right versus left hand imagery
- CSP finds a matrix of spatial filters
 - the variance of the filtered data for one class is maximized
 - variance of the filtered data for the other class is minimized
- CSP filters can significantly enhance discrimination ability between the two classes

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} \\ x_{2,1} & x_{2,2} & x_{2,3} \\ x_{3,1} & x_{3,2} & x_{3,3} \\ \vdots & \vdots & \vdots \end{bmatrix}_{N \times T}$$

Common Spatial Pattern

Input: $\{X_c^i\}_{i=1}^K$ C : classes, i : trial, K : no. of trials.

$X_c^i \rightarrow N \times T$ [No. of channels + Time samples]

Assuming X_c^i is centered & scaled

Goal: - Spatial filter Matrix ' W ' $\rightarrow N \times M$

Transform signal according to eq :-

$$x_{CSPL}(t) = W^T x(t) \quad \text{--- (1)}$$

X -Matrix

DC-Vector

Common Spatial Pattern

Two class conditional covariance Matrix

$$R_c = \frac{1}{K} \sum_i x_c^i (x_c^i)^T$$

for $c \in \{1, 2\}$

determining w as

$$w^T R_1 w = \lambda_1$$

$$w^T R_2 w = \lambda_2$$

$$\begin{bmatrix} \lambda_1 & & & \\ & \ddots & & \\ & & \ddots & \\ & & & \lambda_2 \end{bmatrix}$$

$$\lambda_1 + \lambda_2 = I$$

$$R_1 \omega = \lambda R_2 \omega$$

Generalized eigenvalue

$$\lambda_1^j = \omega_j^T R_1 \omega_j \rightarrow \gamma_1$$

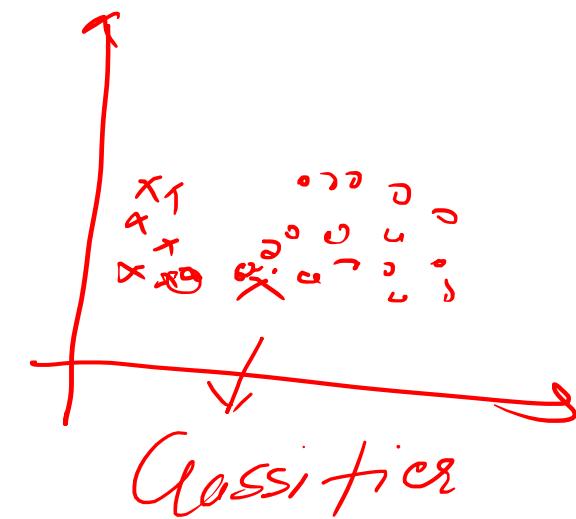
$$\lambda_2^j = \omega_j^T R_2 \omega_j \rightarrow \gamma_2$$

$$\lambda_1^j + \lambda_2^j = 1$$

High value
High variance

Low value

Low variance



CSP applied to EEG for Right/Left Hand Imagery

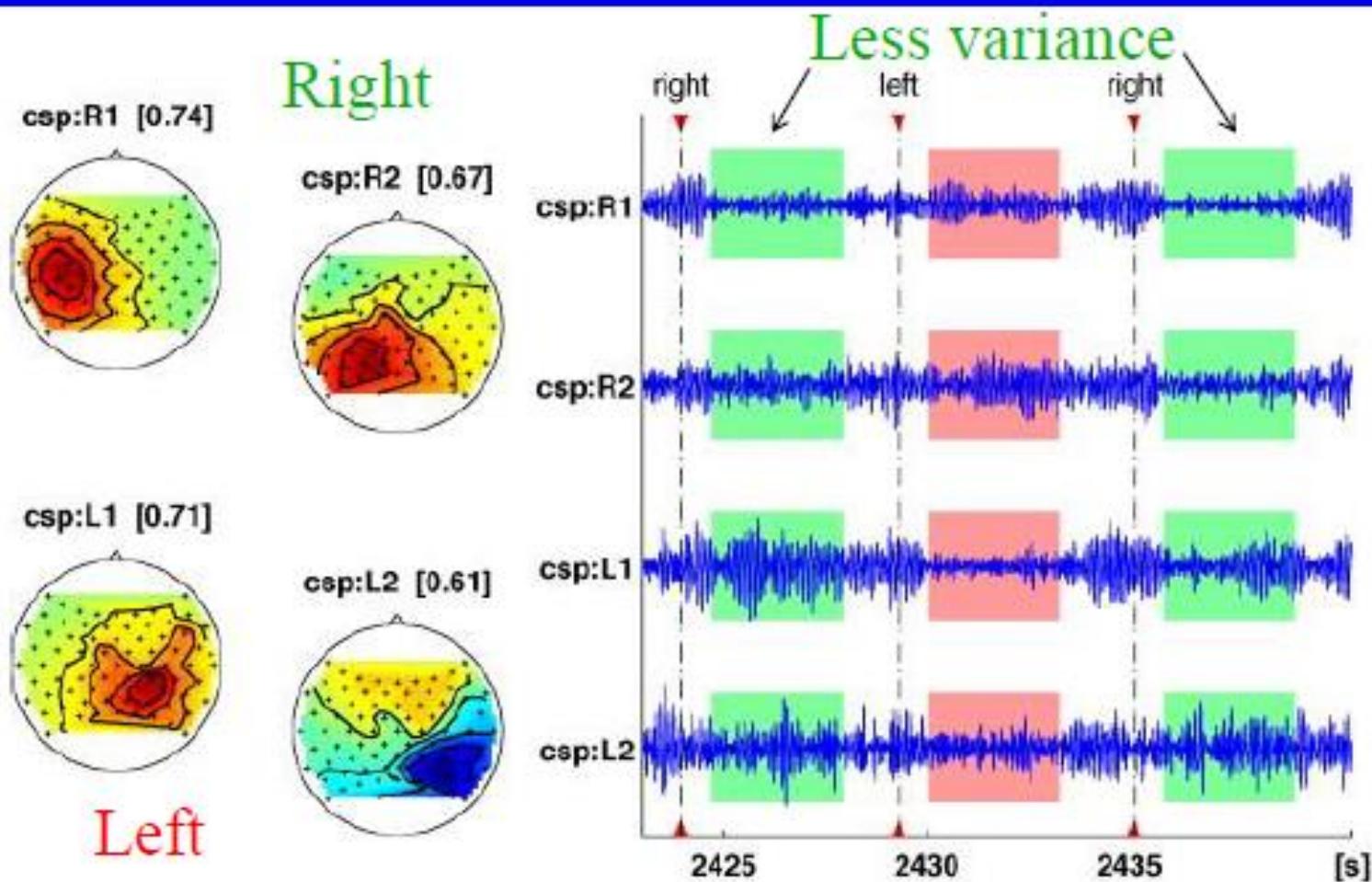


Image source: <http://www.sciencedirect.com/science/article/pii/S0165027007004657>

Artifact Reduction Techniques

- Artifacts in BCIs are any undesirable signals
 - Artifacts outside body-50/60Hz
 - Power line
 - External electrical interference
 - Artifacts within body
 - Rhythmic artifacts due to respiration and heartbeat (the latter are called electrocardiographic or ECG artifacts)
 - Signal distortion or attenuation due to skin conductance changes
 - Eye movement and eye blink artifacts (also called electro-oculographic or EOG artifacts)-- range 3–4Hz
 - Muscle artifacts (electromyographic or EMG artifacts)-- 30Hz or higher frequency range.

Artifact Reduction Techniques

- Thresholding
 - If the magnitude or some other characteristic of a recorded EOG or EMG signal exceeds a pre-determined threshold, the brain signals recorded during that epoch are deemed to be contaminated and rejected.
- Band-Stop and Notch Filtering
 - Band-stop filtering is a useful artifact reduction technique that attenuates the components of a signal in a specific frequency band and passes the rest of the components of the signal.
 - A notch filter set to the 59–61 Hz band (in the United States) for filtering out the 60 Hz power-line noise artifact.

Artifact Reduction Techniques

- Linear Modeling
 - A simple way of modeling the effect of artifacts on a recorded brain signal is to assume that the effect is additive.
 - For example, if $EEG_i(t)$ is the EEG signal recorded from electrode i at time t , then a model of how the signal has been contaminated could be:

$$EEG_i(t) = EEG_i^{true}(t) + K \cdot EOG(t)$$

- $EEG_i^{true}(t)$ is the uncontaminated (“true”) EEG signal from electrode i at time t , $EOG(t)$ is the recorded EOG signal at time t and K is a constant.
- Given an estimated value for K , one can obtain an estimate of the true EEG signal using:

$$EEG_i^{true}(t) = EEG_i(t) - K \cdot EOG(t)$$